Assessing the Role of Landuse Landcover Transition Factors in Mitigating Surface Urban Heat Risk

A Study on Dhaka North City

Mushfik Jalal

A thesis submitted for the Joint programme of
Master in Urban Climate & Sustainability

September, 2022

<table>
<tr><td rowspan="2">Author
Jalal Mushfik</td><td>Publication type
Thesis</td><td>Completion year
2022</td></tr>
<tr><td colspan="2">Number of pages: 96</td></tr>
<tr><td>Supervisor I
Prof. Rohinton Emmanuel</td><td colspan="2">Supervisor II
Dr. M. Dolores Basallote</td></tr>
<tr><td colspan="3">Title
Assessing the Role of Landuse Landcover Transition Factors in Mitigating Surface Urban Heat Risk: A Study on Dhaka North City</td></tr>
<tr><td colspan="3">Degree: Master in Urban Climate & Sustainability</td></tr>
</table>

Abstract

The aim of the research is to support policy guidelines in mitigating surface urban heat risk of Dhaka North City. The urban population of Bangladesh has increased by nearly ten times since independence, one third of which has taken place in Dhaka. During 1974 and 2017 the population of Dhaka grew at an annual rate of 5.4 % per acre. On the other hand, the city has witnessed a rise in temperature of around 3 °C in the last 20 years. Whereas the world is trying to limit the increase in global temperature within 1.5 °C. US EPA blames pattern of urban growth for the heat island effect across all around the world. Urban built-up areas are likely to transform natural landcover such as vegetation and water which causes disturbance in heat budget and tends to concentrate within urban area because of urban geometry. However, the growth of urban depends on the level and type of land consumption by population. Therefore, it is necessary to consider both physical and socio-economic factors to get informed about the pattern of heat increase on urban surface. This study analyses the pattern of Landuse Landcover (LULC) transition from 2001 to 2021 and interaction between socio-economic & physical factor in each administrative unit of the city. The spatial analysis output generates idea about how the land transition and socio-physical factors are combinedly contributing to increase of surface urban heat risk. Landsat 5 TM and Landsat 8 OLI sensor has been used to extract information about surface temperature and LULC transition for the decades of 2001, 2011 and 2021 respectively. GIS data and Statistical information from Capital Development Authority (RAJUK) and Bangladesh Bureau of Statistics (BBS) have been used to develop socio-economic and physical index of respective Thana areas of Dhaka North City. Using a Multi-Layer Perceptron (MLP) Neural Network model, the study also predicts susceptible LULC transition pattern of surface heat increase for the year of 2031 and 2041. To propose mitigation strategy for next 20 years, the study incorporates existing influential socio-economic and physical factors of surface heat reduction along with predicted susceptible areas of gradual heat intensity. This integrated approach of urban transition factors provides information about probable trend and distribution of heat propagation led by land transformation as well as potential approach and tool of heat mitigation. In this way, the proposed policy guidelines of heat mitigation paves the way to utilize capacity of existing resources and suggest best alternatives for Surface Urban Heat Island (SUHI) mitigation for the Dhaka North City.

Keywords

SUHI, Landuse Landcover Transition, Socio-economic Factor, Physical Factor, Mitigation

Originality statement. I hereby declare that this Master's dissertation is my own original work, does not contain other people's work without this being stated, cited and referenced, has not been submitted elsewhere in fulfilment of the requirements of this or any other award.	**Signature**

TABLE OF CONTENT

ACKNOWLEDGMENT

Firstly, I would like to thank to my supervisor Professor Rohinton Emmanuel. I am particularly grateful for continuous support during my thesis work.

I received kind support from data providing organization. I am grateful to them for spending valuable time on sharing data with me.

I want to offer my special thanks to MUrCS family and specially all my batchmates who have a source of inspiration throughout the MUrCS experience.

I am particularly grateful to them who contributed their knowledge in my research. Raju, Rabeya, Zarin, Newsha, Shayantoni, Fernanda, Kawser and Fahad.

I will be forever grateful to Dr K. Z. Hossain Taufique and Tamzidul Islam who gave foundation of my conceptual knowledge and technical expertise beyond academic curriculum.

And finally, I want to acknowledge enormous support from my mother, wife and, especially my father whom I lost during my journey of this Thesis.

LIST OF FIGURES

LIST OF TABLES

ABBREVIATION

BBS	Bangladesh Bureau of Statistics
CA	Cellular Automata
DAP	Detail Area Plan
DEM	Digital Elevation Model
DNCC	Dhaka North City Corporation
DSCC	Dhaka South City Corporation
GDP	Gross Domestic Product
GIS	Geographic information System
HH	Household
IPCC	Intergovernmental Panel on Climate Change
JICA	Japan International Cooperation Agency
LST	Land Surface Temperature
LULC	Landuse Landcover
MLP	Multilayer Perceptron
NDVI	Normalized Difference vegetation Index
NLST	Normalized Land Surface Temperature
OLI	Operational Land Imager
RAJUK	Rajdhani Unnayan Katripakkha
SHLC	Centre for Sustainable, Healthy and Learning Cities and Neighbourhoods
SVF	Sky View Factor
SUHI	Surface Urban Heat Island
TM	Thematic Mapper
UHI	Urban Heat Island
UNDESA	United Nations Social Development Network
US EPA	United States Environmental Protection Agency

CHAPTER 1: **INTRODUCTION**

1.1. **Rationale of the study**

The scientific community mutually agrees on the matter that the Earth's climate is warming since the beginning of industrial era, and it is evident that the warming phenomena has risen significantly in last 50 years. On the other hand, through the process of Urbanisation, significant modification of local climates occurs, and the most visible phenomena of it is Urban Heat Island (UHI) (Champan et. al., 2017). Tackling the combined effects of global warming and urban heating is one of the biggest challenges to be faced by world sustainable thinkers (Parker, 2004). The percentage of world urban population is increasing rapidly and expected to reach nearly 70% by the year of 2050 as projected by UNDESA (2015). At the same time, there is a continuous change of global climate at an unprecedented rate (IPCC, 2014). National Centres for Environmental Information states an decadal increase of global annual temperature at an average rate of 0.14°F since 1880, which is estimated almost double (0.32°F) since 1981. Stewart (2011) finds that more than 1100 cities across the world are facing various degrees of UHI intensity, irrespective of their climatic zone, city size or geographical position.

Urbanisation processes inevitably replaces impervious surfaces and causes difference in thermal energy balance (Li et. al., 2019). Artificial urban fabrics such as buildings, roads, and other infrastructure absorb and re-emit the solar radiation more than natural landscapes like water bodies and vegetation. As estimated by US EPA, due to higher concentration of artificial urban form compared to lower level of natural features, temperature anomaly appears during both day and night, which accounts for around 1–7°F and 2-5°F higher temperatures in urban than that of outlying areas respectively. There are several climatic, physical and socio-economic factors which are influencing UHI intensity in particular zone of urban area (Giridharan & Emmanuel, 2018; Manoli et. al., 2019).

According to Met office, average annual temperatures of Bangladesh are projected to rise by 1.0°C to 1.5°C by 2050, even after maintaining compliance as recommended by the Paris climate change agreement of 2015. The situation would be worst if the preventive measures are not taken by as per Paris agreement. (Mani, et. al., 2018). Dhaka the primate city and capital of Bangladesh has been experiencing rapid population and spatial growth since its independence. The Dhaka Structure Plan report indicates an increase of 0.5 ° C annual average temperature in Dhaka by the last 100 years. A recent study conducted by Moniruzzaman in 2021 shows the decadal growth of built-up area is always increasing whereas all the other features like green space and water bodies are diminishing in expense of built-up areas in every decade at a rate of 40% since 1978. Economist have warned that, Cities might lose up to 11% of economic output due to UHI effect. apart from adverse environmental effect, the phenomena also cause harm to human health and well-being in terms of heat-related morbidity and mortality (Li et. al., 2021). Therefore, to control the increasing pattern of UHI effect an immediate action needs to be taken by concerned authorities through strategic and climate sensitive urban development plan.

1.2. **Aim and Objectives**

The aim of this research is to find the pattern of urban growth factors contributing increase of surface heat and how the factors can be utilized to reduce the risk of increasing heat intensity. The objectives of the study are

1. To Identify the pattern of LULC transition and its effect on Surface Temperature change.
2. To measure relative influence of physical and socio-economic factors contributing heat intensity of urban surface.
3. To predict location of susceptible land transformation causes rapid surface heat increase.

1.3. **Research Question**

1. What major types of spatio-temporal transition of Landuse Landcover (LULC) does affect the increase of surface temperature across the city?
2. What is the pattern of socio-economic and physical factor influence on surface temperature rise.
3. How the factors of urban transition can be managed in context of Landuse Planning to control the adverse impact of heat risk?

1.4. **Outline of the Methodology**

The foundation of methodology is based on quantification of Land Surface Temperature (LST), areal transition of Landuse Landcover (LULC) classes and index of factors (Socio-economic & physical) index. The study considers maximum surface temperature scenario for finding underlying pattern of LULC transition and factor of influence. This methodology of this research assumes, the identifies pattern results in UHI effect for the geographic extent because it occurs within the distinct range of maximum surface temperature increase. The methodology also follows a standard scale of measurement to bring all the variables of different unit in a common scale of measurement.

1.5. **Structure of Dissertation**

The dissertation is divided into seven chapters as stated below –

Chapter 1: This Chapter of dissertation shares the foundation and principles of the research topic. It includes the global and local scenario of increasing pattern of UHI effect. The repercussion of UHI effect for the study area, and why the solution of the problem is necessary in context of Dhaka, are the key areas of discussion in this chapter.

Chapter 2: Chapter 2 discusses about previous studies on the related topic. This chapter talks about all the relevant concepts, methods and key findings of previous studies on mitigation strategies, influential factors and urban landcover formation associated with Surface Urban Heat Island (SUHI). At the end, it also provides the idea about novelty of this research.

Chapter 3: Chapter 3 depicts the preliminary idea about study area. The historical growth, legislative formation, administrative division of the study area is the topic of discussion in this Chapter. It also presents base map of the study area and provide information about geographic division of research unit.

Chapter 4: This chapter provides all the necessary information about how information has been produced by using what kind of tools and techniques. The chapter also talks about justification of selected variables and the process of predicted model validation as well as accuracy assessment of LULC class.

Chapter 5: This chapter presents the analytical outcome of the research. It disseminates readers about how the changing pattern of LULC classes is affecting surface heat change. It also reveals the contribution level of influential factor of heat intensity.

Chapter 6: This chapter comprises of steps by step process of mitigation strategies. It describes the quantitative and qualitative information of risk reduction parameters. It also gives the foundation to formulate logical framework of strategic process as well as discussed about components of heat mitigation.

Chapter 7: This is the final chapter of this study representing concluding remarks based on results and findings. The chapter also states limitation and further scope of research.

CHAPTER 2: LITERATURE REVIEW

2.1. Form and Aspect of Urban Heat Island

The concept of urban heat island (UHI) refers to the phenomena that an urban area is significantly warmer than its surrounding rural areas due to human activities. This concept of UHI can be considered as one of the most unambiguous and flawless example of climate change due to anthropogenic sources (Hanna et. al., 2011). As quoted by Richard S.J. Tol MAE, Professor of Economics at the University of Sussex, "Any hard-won victories over climate change on a global scale could be wiped out by the effects of uncontrolled urban heat islands. Urban Heat Island is usually measured by two form of indicators such as Surface Urban Heat Island (SUHI) and Atmospheric Urban Heat Island (AUHI) (Derdouri et al., 2021). AUHI is further categorized into canopy layer and boundary layer to study air temperature below and up of urban building height (Voogt & Oke, 2003). It is important in heat island study to specify which indicator is used to describe Heat Island Effect. There are several aspects influencing AUHI and SUHI and affect the intensity and magnitude differently. For example, Yuan & Bauer (2006) in day time SUHI intensity is prominent, whereas AUHI is noticeable at night. So, study associated with SUHI considers daytime surface temperature to record max intensity scenario. Regarding seasonal aspect, SUHI is greater during summer and lowest during winter (Imhoff et al. 2009). Often thermal comfort may be misunderstood with surface heat intensity level. It is important to understand that thermal comfort is directly related with air temperature, but it can be indirectly described by SUHI as both are highly correlated and proportionate (Sharma & Joshi 2014; Yuan & Bauer 2006). Because of different heat transfer properties, SUHI intensity tends to be higher as stated by Grimmond (2007).

2.2. Heat Mitigation Strategy

It is well established concept that LULC changes in urban area are triggering UHI effect and over the time the phenomena are rapidly increasing. To achieve sustainable and resilient urban development, there is no other alternative than implementation of Landuse Planning. Pal & Ziaul (2017) finds dense urban characteristics strongly influence an increase of LST and urge for decentralization to release the pressure on urban land. More specific recommendations on mitigating UHI effect are associated with conservation of greeneries & waterbody, using cooling surface material for roof and pavement. A few studies also talk about indirect measures such as dependency on renewable energy and promoting incentives like carbon credit (Kikon et al., 2016). Yet, there should be some consideration need to be chosen while implementing mitigation effort in a city. In a study by Priyankara and others (2019) suggests greening should be developed in both horizontal and vertical direction to balance green surface fraction and shading. in case of waterbody, Cai et al. (2016) proves that aggregated wetland patches are more effective in lowering LST than fragmented one. However, Ghosh & Das (2018) reveals complex nature of greeneries and waterscape by analyzing cooling island effect. The study finds the cooling effect of greeneries encompasses larger area than waterscape, but water area provides more cooling effect within its boundary. Apart from implications of physical factors, there are socio-economic drivers which triggers UHI effect in urban area. A recent research paper finds that, socioeconomic factors explains approximately 10 % to 20 % of the variances of UHI (Ying et. al., 2020). This findings implies that the contribution of socioeconomic drivers need to evaluated for heat mitigation strategy. Therefore, a combination of both factors is encouraged to mitigate UHI effect.

2.3. Methods of LST retrieval and LULC Classification

Satellite based remote sensing has become popular for retrieval of LST and extracting LULC information with advancement of earth observation and computation system. Compared to ground-based temperature data collection, satellite-based data has been proved more time and budget consuming specially in meso, macro and local scale, along with its benefit for open access historical archive data (Derdouri et al., 2021).

Moderate resolution Landsat and low-resolution MODIS are most common data sources used for LST retrieval, but they have different scope of output as per spatial and temporal resolution. Dewan and others (2021) use MODIS data to find diurnal surface temperature comparison between different cities of Bangladesh, because MODIS satellite crosses twice (both day and night) in a day. Whereas Landsat can be used for seasonal, annual or decadal study only because of its 16-day temporal resolution. But Landsat provides more detail spatial information and hence became mostly used source for city scale study (Mahmood & others 2019; Bala et al., 2021). Rigo and others (2006) also justifies the statement of different scope for using of respective sensor, along with an estimation of LST accuracy for Landsat (1.2 K) , MODIS (daytime 1.3 K & nighttime 0.7 K) and NOAA (2.3 K). Imhoff & others (2009) suggests satellite derived LST represents less bias than encountered by ground based LST.

In quantifying SUHI normally 2 steps are followed such as 1) retrieve LST as proxy of surface temperature and 2) calculating LST differences between variety of indicators like urban-rural, urban-agriculture, urban-water, difference by admin boundary etc. (Scwarz et al., 2011). However, many studies did not use LST differences and depended on sole LST value to represent surface temperature assuming the fact that LST is correlated with surface properties associated with LULC (Feng et al., 2014; Pal & Ziaul, 2017). Regarding retrieval method of SUHI, Li et al., (2014) mentioned about three types of method depending on Land Surface Emissivity (LSE) and Atmospheric Quantity are known. Single Channel (SC) Algorithm (Zhao et al., 2013) are mostly used in literatures dealing with Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper (ETM). On the other hand, Multi-channel (MC) algorithm is used in studies dealing with multiple adjacent thermal sensors like Landsat 8 OLI (Zhao et al., 2013). Among all the variants of SC and MC, Mono-window (Qin et al., 2001) and split-window algorithm (Derdouri et al., 2021) are mostly employed in the previous studies respectively.

LST is spatially and temporally dynamic. There is anomaly in LST values during different seasons and at different Landuse types (Sharma and Joshi, 2014). Many researchers use absolute LST value to calculate UHI mostly in cases of analyzing seasonal and diurnal output. But when it is necessary to represent annual LST with effect of seasonal and diurnal variation, a Normalized or Upscaling approach is undertaken (Verma & Garg, 2021; Huang et al., 2016).

As like LST, satellite sources are also used to extract LULC information of a geographic area. as discussed earlier, because of certain specification Landsat is also popular in the same way for classifying LULC. To define Land classes, authors use either i) q combination of own expertise and other expert’s knowledge, ii) classification scheme by agencies, iii) unified classification system, iv) inventories of scientific institutions. Moreover, some studies expand land class to more representative classes to evaluate simplified impact of LULC class on SUHI. For example, Huan & Wang (2019) elaborated Land classes into residential, commercial, industrial etc. to analyze the impact of human activity on urban temperature. Similarly, Tran et al., 2017 describes heat impact according to different urban development types such as infill, extension and leapfrog.

Regarding classification method, both parametric and non-parametric have been used in previous literatures with support of pixel, sub-pixel and object-based classification tools. Parametric includes supervised and unsupervised techniques whereas non-parametric includes machine learning algorithm such as neural network (NN), support vector machine (SVM), random forest (RF), and k-nearest neighbor (kNN). SVM is mostly recognized for its higher accuracy which is used by Faisal et al., 2021, with a high accuracy output. The study also applies NN in predicting urban thermal scenario for the city. On the other hand, in case of parametric method both supervised and unsupervised is adopted and the output have been found with high accuracy as estimated by error matrix. Dey et al., 2021 simulated LULC change model with background Landcover base year data extracted by maximum likelihood classification algorithm of supervised classification. On the other hand, unsupervised technique has been applied in many cases for classification using Iterative Self-Organizing (ISO) tool (Thanh et al., 2018; Wang et al., 2016; Mohamed, 2017). Regardless of classification method, validity is assessed by overall accuracy, user accuracy, producer accuracy and kappa statistics and excellent accuracy is defined by greater than 85% for every case (Dey et al., 2021). Variety of data sources are used for validation purpose like GPS field survey (Mallick et al., 2013), high resolution aerial (Li et al., 2012) or satellite imagery (Zhang et al., 2017). However, google earth has outperformed all other traditional sources by its reliability as well as time and cost effectiveness (Dihkan et al., 2018).

2.4. Assessing Linkage between LULC and LST

The major driver behind changing pattern of surface temperature is Landcover and Landuse change. Therefore, finding nature of relation between these two phenomena has drawn attraction to many authors dealing with UHI effect. Suriana and Others (2020) finds an upward trend of LST over the years during 1989 to 2018, with a significant role of built-up area for increasing LST intensity. There are some Landcover properties causes the changes in heat properties resulting surface temperature increase through different heat storage and conductive capacity. Ke and others in 2014 investigated impact of Landuse Landcover properties and finds latent heat flux is the dominant factor in changing thermal behavior followed by net radiation. The authors also find sustainable economic scenario of southern Jiangsu city in China helps in reducing monthly average temperature. Although LST is highly correlated with Landuse distribution such as LST hotspot in industrial and commercial area, while cold spot is clustered in parks and water bodies as shown in a study by Tran et al., 2017. He also concludes that, there is a nonlinear relationship between LST and LULC because of complex landuse structure and variability due to climate. There are few studies predicted surface temperature using machine learning technique. For instance, Faisal et al., 2021 simulated LST and UTFVI for the year of 2030 and found an increase in 13% (summer) & 20% (winter) surface temperature, and around 70% of total land in study area will be occupied by stronger UTFVI by 2030. The authors also predict the growth scenario of built-up and vegetation index and shows that LST situation will become worse through simultaneous increase of impervious surface with decrease of vegetation cover.

The nature and pattern of interrelationship have been further assessed using different statistical method. Regression is mostly used by authors to model relationship between LST and LULC factors. geographically weighted regression (GWR) is found effective in most cases because of its analytical ability to address spatial variation across surface (Zhou & Wang, 2010). However, ordinary least square (OLS) methods is proven efficient for regional scale heat island study (Deilami, 2016). Chart analysis is another method representing relation of mean LST and LULC defined by zonal boundary (Mallick et al., 2013). Correlation is another used methos helpful for quantifying strength and direction of relation between LST and LULC factors. Although Pearson correlation (Kikon et al., 2016) is commonly used method applied in literatures, however other type of correlation such as Kendal rank is helpful in detecting monotonic dependence between variables as well as the coefficient support in resistance against missing value and outliers (Fan et al., 2017). Therefore, selecting types of correlation method depends on the nature of interrelation between the factors. concentration ratio is another type of LST impact assessment method mainly illustrating LULC categorical contribution to UHI effect. Dutta and Das (2020) find positive and negative effect of respective LULC on SUHI. This study finds an interesting fact about LST intensity and distribution. LST is higher during first several period because of heat agglomeration in certain area, whereas later on heat effect decreased as there were sparse distribution of heat islands. Pramanik and Punia (2020) further simplified concentration index into Landscape index and assess contribution of LULC for heat sink and heat source of the study area.

2.5. **Factors affecting LST**

While LULC change from pervious to impervious i.e. natural to urban is considered as main driver for increasing LST (Tran et al., 2017), during all around the year regardless of season (Pal & Ziaul, 2017); there are some studies investigated root causes of LST by going into detail of LULC factors. Physical factors are analyzed in most of the cases including impervious surface (IS), vegetation, waterbody and urban morphology etc. For instance, Xiong et al. (2012) determines that location of high LST in dense built-up and industrialized areas using

Normalized Differential Built-up Index (NDBI). On the other hand, Kant et al., (2009) uses Normalized Differential Vegetation Index (NDVI) and Fractal Vegetation Cover (FVC) for assessing impact of green physical factors on LST and finds a negative relationship. Apart from individual factor assessment, urban geometry is also analyzed in several research to investigate dynamic aspect of single factor as defined by its complex formation over the surface. Huang & Wang (2019) analyzed effect of 3D urban form on LST in two different zones such as urban and non-urban. The study find 2D urban morphology is strongly correlated with LST than 3D metrices, explaining complex interaction of urban geometry with thermal properties. For example, higher SVF enhance air circulation and lower SVF helps in reducing incoming solar energy, therefore both contributing cooling effect but with opposite value. Furthermore, high rise building increases the possibility of heat absorption but at the same time it counteracts SUHI with shadings effect and the study proves the statement through finding negative correlation between LST and building height.

There are few studies dealt with socio-economic factor and considered population density as a factor influencing LST. Zhang et al. (2017) finds that with high population density there is an increase of LST. The similar result is also evaluated by Deilami et al. 2016 and argue that population density is positively correlated with LST increase, although the research suggest porosity is comparatively stronger predictor than population density. Similarly, Zhang et al., also describes that, LST changes are more related to socio-economic activities (domestic household and workplaces) of the area rather than total number of populations of that location. However, some other socio-economic factors such as house rent (Chen et al., 2012) and Gross Domestic Product (Cui & Shi, 2012) has been used in the research and finds positive relationship with LST increase. Usually, socio-economic factors are overlooked because of data lacking. According to Bangladesh Bureau of Statistics (BBS) , there are variety of socio-economic data available covering necessary information which might be helpful to analyze LST impact. However, maximum of them is collected at district and country level, that would support for regional or global scale study. A few information is available at ward or community level such as no. of household, electricity consumption and building materials and these might be considered to assess LST impact for cities of Bangladesh.

2.6. **Knowledge Gap**

Mitigation measures of UHI depends on the respective city characteristics i.e. local climate, geographic setting and city size etc. therefore, it is important to propose mitigation strategy considering study area specification along with addressing existing Plan Proposals by City Development Authority. While other literatures explain importance of respective cooling features as a general consideration across different cities in different climatic region, this study considers specific requirement at local administrative level according to its heat profile and resource capacity. So that, local government institution gets the idea of the existing climate sensitivity prevailing within their jurisdiction and what measures of development activity should be proposed according to the given strategies associated with social and spatial development. Furthermore, decadal spatio-temporal analysis helps in finding historical policy gaps towards ensuring sustainable land transformation. In this context, the study tries to find dynamic temporal land transition pattern of three different decades to include the type of intermediate effect of spatial transition. Whereas other studies describe the static nature of LULC impact in terms of areal coverage of particular land class within the area over the decades. Thus, the study takes the effect of LULC a step further by analyzing its composition of growth. Theis study also investigates the causes of surface heat intensity by comparing relative contribution of not only physical but also socio-economic factors. Previous studies only focused on analyzing correlations of different variables of socio-economic and physical factors with LST change. However, none of them deals with identifying the accumulated contribution of individual factor towards surface heat intensity. This study compares their relative importance and tries to find the pattern which helps to understand which factor has a grater collective impact on growing pattern of surface heat. In this way, the outcome categorizes area of strategic priority and identify leverage variable to mitigate heat island as per neighborhood level characteristics.

CHAPTER 3: DESCRIPTION OF STUDY AREA

3.1. Urban Growth of Dhaka City

Dhaka is a historical capital city of Bangladesh which has a long trend of increasing rapid population density. After independence in 1971, due to prioritize economic opportunity and establish administration center in capital Dhaka, the city could not control its rural and semi-urban population to be migrated (Kamal, 1993). Currently, the capital is sharing 40% of total country's GDP leading the country towards achieving economic development at a rate of 7.4% annual growth in National GDP, ranked among top fastest growing economies in the world (World Bank, 2016-2020). However, capital authority of Dhaka could not control its spatial and population growth resulting one of the most densely populated cities in the world with primacy status ranked as 9 in the world (World Bank, 2010). Being in a suitable geographic location and nearest proximity with other major cities (Figure 1), Dhaka has also become the Centre for Transport, Education, Cultural and Political activities.

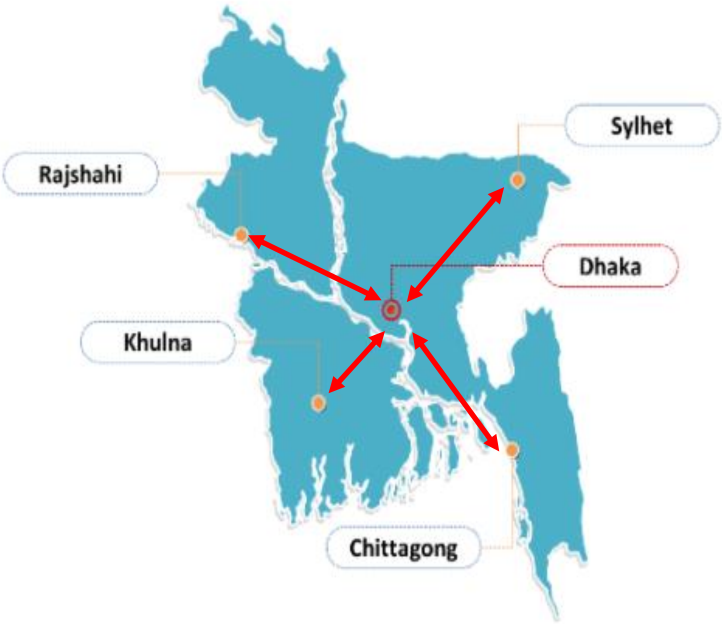
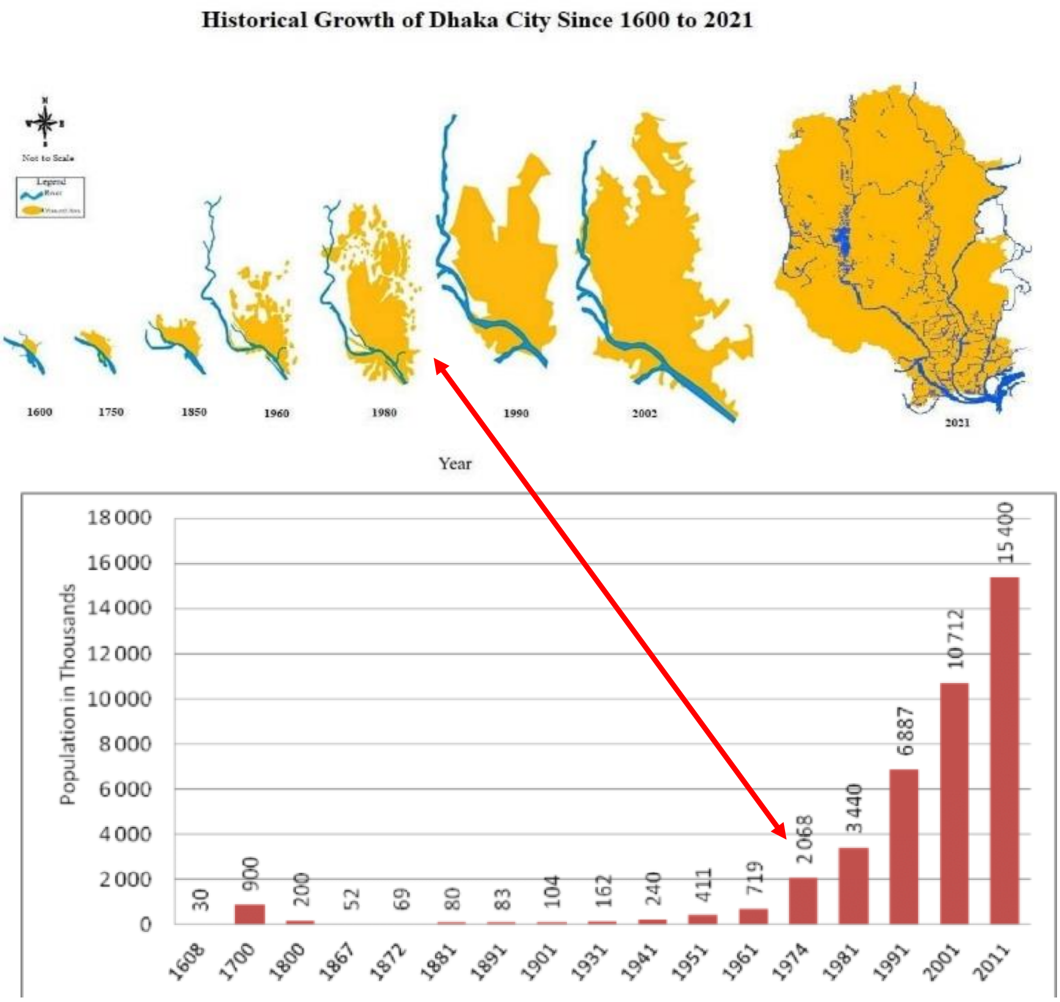


Figure 1: Location of Dhaka City

Figure 2 explains comparative growth of Dhaka city in terms of demographic and spatial. Since its birth in 16th century (Kabir, 2012). The population growth was sluggish before 1974 and during 1974 according to Bangladesh Bureau of Statistics (BBS) the total population was 2.68 million. After 1974 (post-independence), population hiked and continuing to grow with a number of 15.4 million in 2011 (BBS, 2011). Looking at spatial growth as given in Table 1, there is a geometric increase of spatial growth pattern of Dhaka city. To accommodate population influx, Dhaka metropolitan administrative boundary has been expanded year to year until preparation of Detail Area Plan for Dhaka in 2010 by Capital Development Authority (RAJUK).



Population Growth in Dhaka Megacity (1608-2011). Source: BBS 1977; 1984; 1991; 1997; 2003; Taylor 1840; D'oyly 1824; Siddiqui 2000.

Figure 2:Comparative growth of Population and spatial boundary of Dhaka City

Year	Area in Sq Km	Areal Expansion in percentage
1974	353	-
1981	510	52
1991	1353	165
2010	1543	1528

Table 1: Area Expansion of Dhaka City (Source: Ahmed et. al., 2014)

Table 2 describes the reason of expansion of spatial boundary of the capital. It shows that, the percentage of annual average growth rate of Dhaka population of Dhaka was higher every time except in 1981. However, the spatial distribution of population density was not same or even fairly distributed across the city. The density is higher in southern part of the city surrounding commercial areas.

Year	Total Urban Population	Total Population of Dhaka City	Urban Population %	Average Annual Growth Rate &	
				All Urban Area	Dhaka City
1951	18,19,773	4,11,279	4.33	1.69	1.28
1961	26,40,726	7,18,766	5.19	3.75	5.74
1974	62,73,602	20,68,353	8.78	6.62	8.47
1981	1,35,35,963	34,40,147	15.54	10.63	7.53
1991	2,08,72,204	64,87,459	20.15	5.43	6.55
2001	2,88,08,477	99,12,908	23.39	3.27	4.33

Table 2: Urban Population growth in Dhaka City compared to all Urban area of Bangladesh (Source: Ahmed et. al., 2014)

3.2. **Landscape Ecosystem of Dhaka Metropolitan Area**

Dhaka city is surrounded by four major inland water bodies namely Briganga river (south), Balu River (east), Turag river (west) and Tongi canal/khal (north). In a study conducted during 1998, only 21% of the total area of Dhaka city is of open landscape type. The total area of this open land is 8668.02 acre (Rahman, 1998). Approximately 30-35 khals or natural drainage, summarizing up almost 437 km in length (JlCA, 1991) together with the four major rivers and canal, crisscrossed by entire dhaka metropolitan area. Apart from these, there are several ponds, urban forests and other green features distributed in scattered way across the metropolitan area. According to The Independent (2017), the current number of public parks and playing fields are 40 and 16 respectively, for such a overcrowded city with 17 million residents (Bangladesh Bureau of Statistics, 2011).

3.3. **Formation of Dhaka North City**

This study is based on urban areas of Dhaka North City. The Dhaka City is divided into two administrative area such as Dhaka North City Corporation (DNCC) and Dhaka South City Corporation (DSCC). The former Dhaka City Corporation (DCC) was dissolved on by The Local Government (City Corporation) Act. 2009, Amendment (2011) 4th December 2011. The geographic extent of DNCC is located within 90 ° 20’ - 90 ° 28’ longitude and 23 ° 44’ - 23 ° 54’ latitude. The DNCC is divided into 54 wards under 10 regions. As after the formation of DNCC on 2011, there is no official census conducted by Bangladesh Bureau of Statistics (BBS) till date. According to recent Waste Report 2019-2020 report of DNCC. It has an area of 196.22 sq km with a total population of 6.1 million, where approximately 31,488 people are living per sq km area. The detail map of DNCC has been presented in Figure 3.

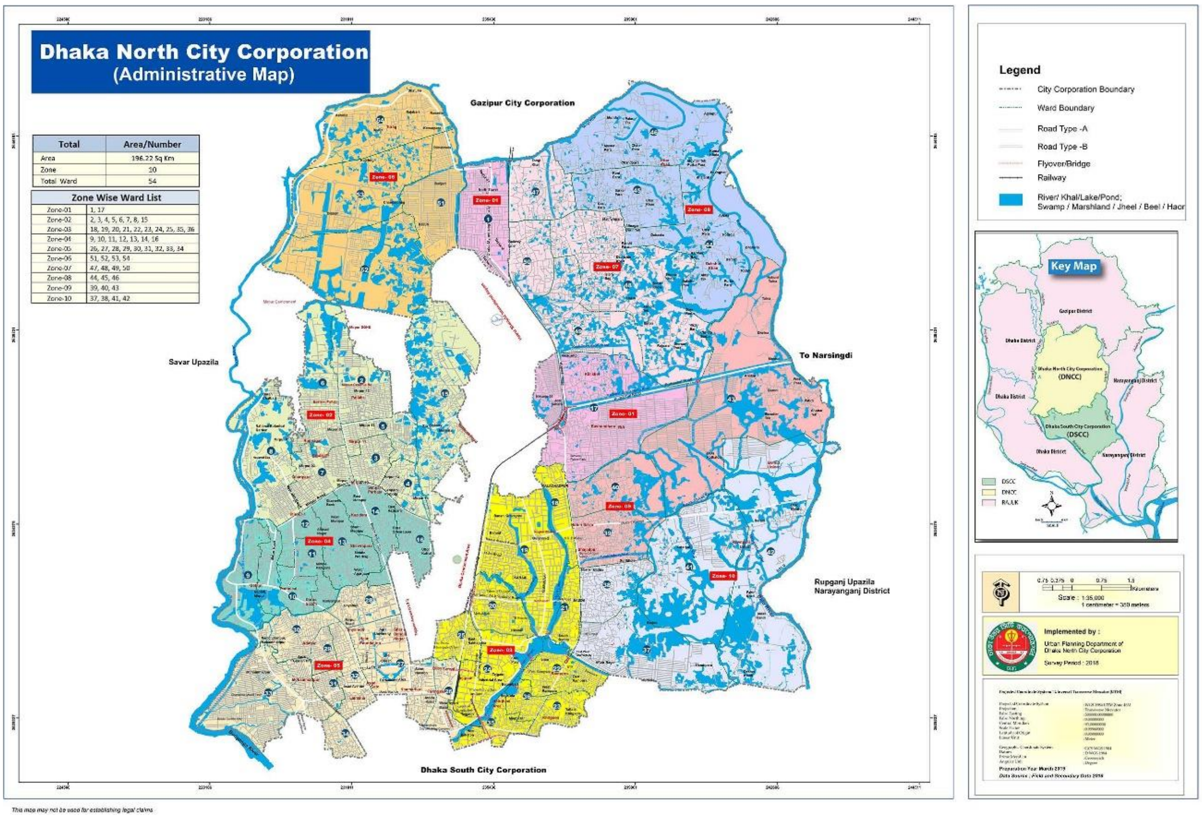


Figure 3: Dhaka Administrative Map (Source: DNCC)

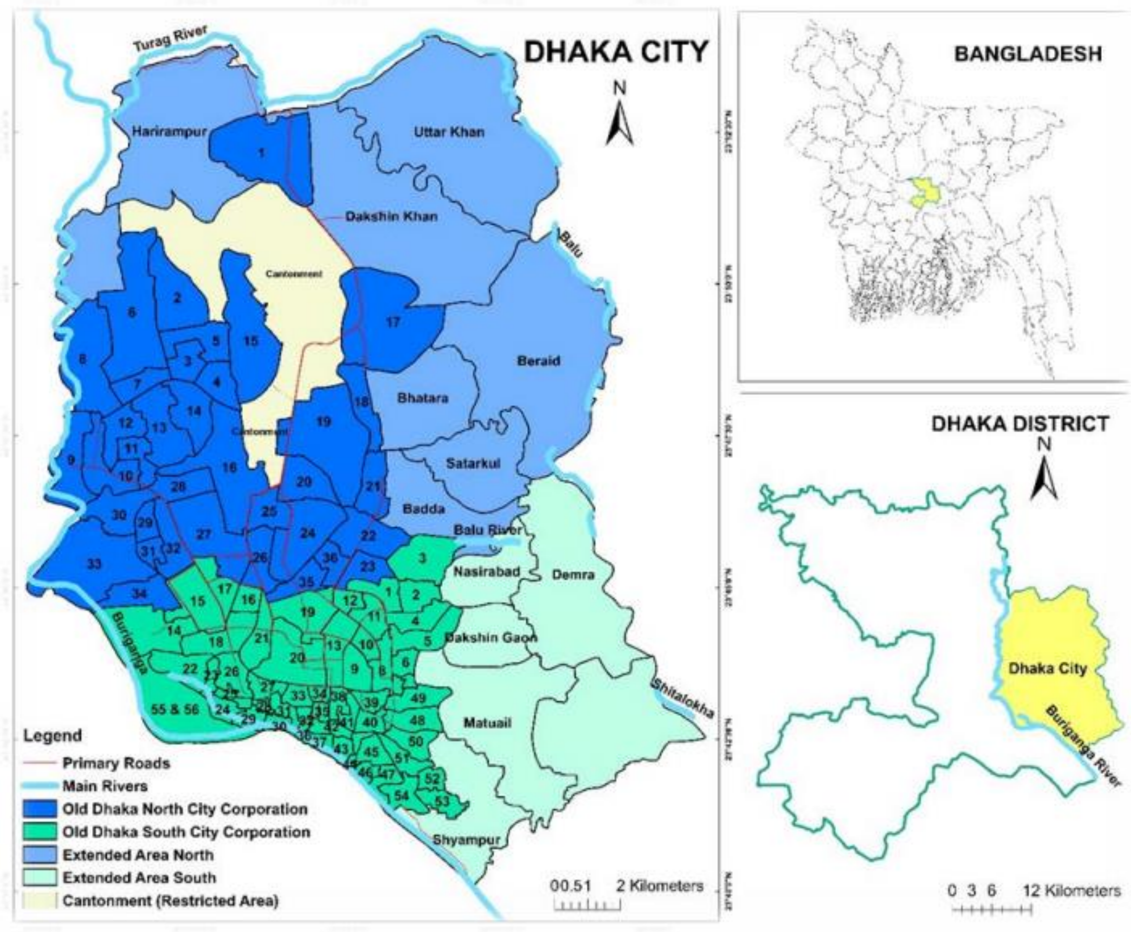


Figure 4: Dhaka City (SHLC,2018)

DNCC was extended on 2016 and new areas have been included within the DNCC boundary. According to Geocode as given in BBS 2011, the old areas are classified as urban and extended areas are either rural or other urban. As sated before this study focuses on urban areas of DNCC and considers statistical boundary of urban wards within each Thana as per definition of BBS 2011.Figure 4 describes the old and extended area of DNCC and DSCC.

According to BBS 2011, urban area DNCC comprises of 18 Thanas including a total of 36 wards. This study considers Thana as a reference administrative boundary for further analysis. Figure 5 shows the map of urban area by Thana boundary of Dhaka North City Corporation.

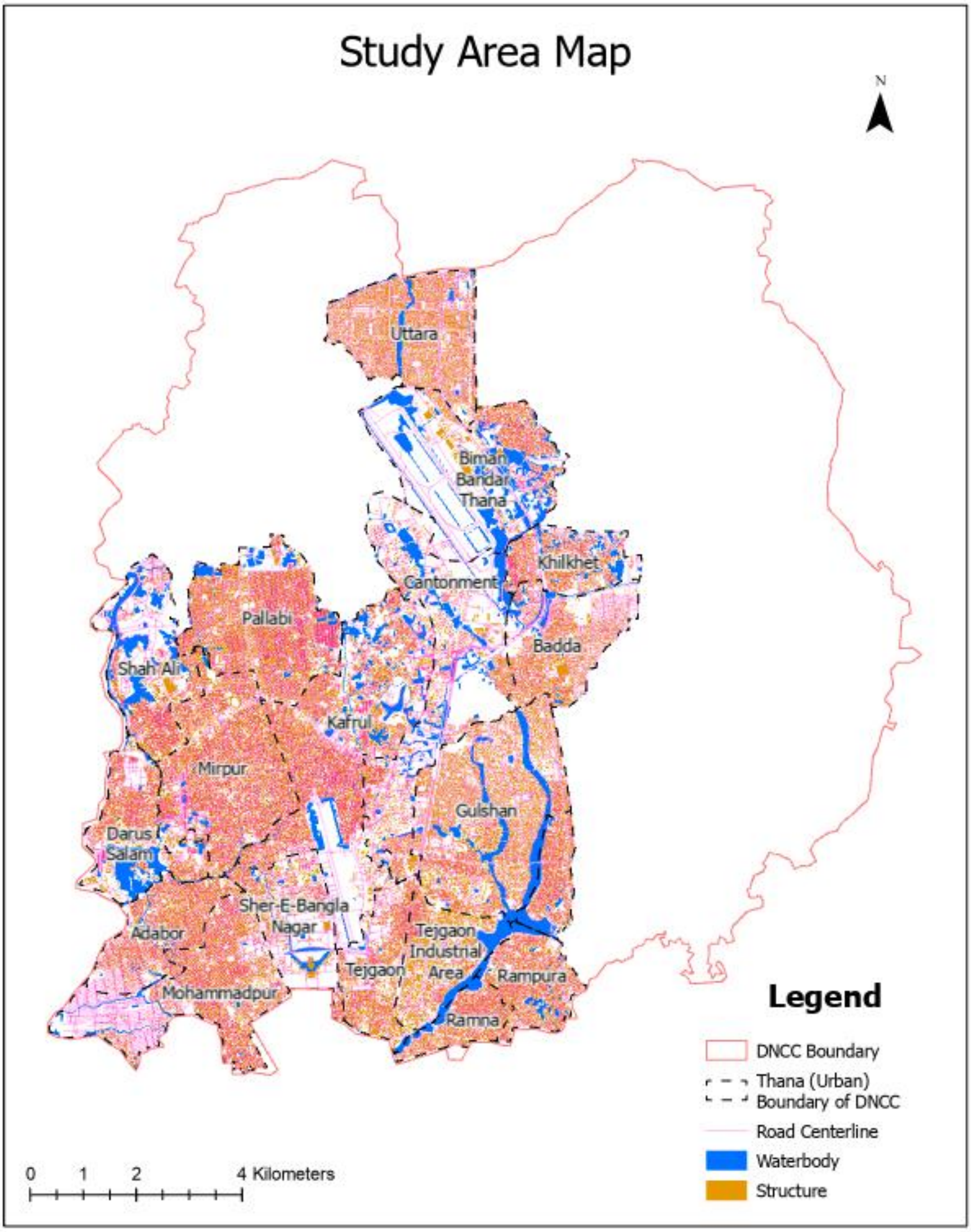


Figure 5: Study Area (Source: GIS data of RAJUK)

CHAPTER 4: METHODOLOGY

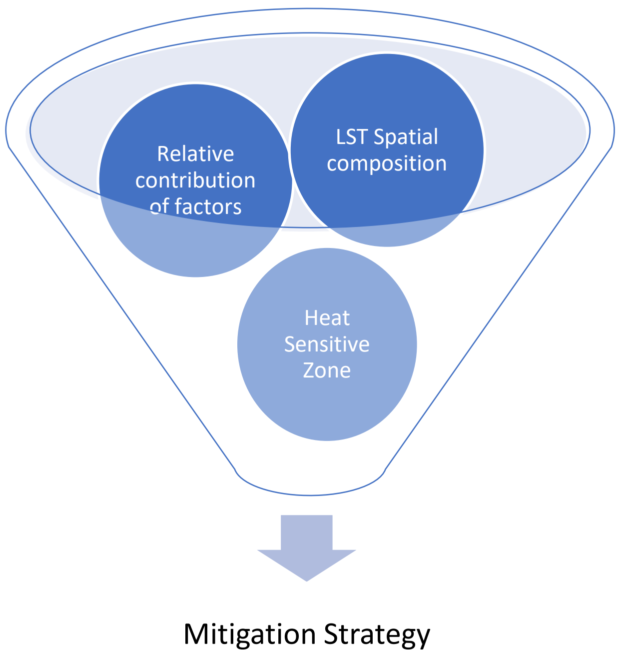
4.1. Approach

The study is based on observational thermal remote sensing approach of Urban Heat Island (UHI) Study (Parham, 2010). In this approach the information of surface temperature is measured through upward thermal radiance by remote satellite sensors (Voogt and Oke, 2003) The main methodological foundation of the study is to prepare base spatio-temporal information of Land Surface Temperature (LST) and Landuse Landcover (LULC) change and then compare the changing surface heat attribute with related physical and socio-economic factors. This Meso scale study is supplemented by micro and local level information of physical and socio-economic features. The analysis of factors has been parameterized in a common scale of measurement to compare impact of factors with surface heat intensity. The administrative city domain size and highest building height have been considered as lateral and canopy layer boundary condition. The study is focused on finding pattern of contributing by individual factors at maximum increase scenario of surface heat.

4.2. Research Framework

Research framework of this study has been developed according to reviewed literature as discussed in previous chapter. The design of this research follows the conceptual and technical framework as depicted in Figure 6. The conceptual framework gives the theocratical foundation of the research, while technical framework deals with the tools and techniques to be used to produce research outcome. Conceptual framework of this study considers three items such as LST composition, factor contribution and heat zone identification and thus provide foundation of heat mitigation strategy from theoretical perspective. To achieve theoretical perspective, necessary tools and techniques are applied to extract LST, classify LULC, prepare factor index and predict urban growth.

(a)



(b)

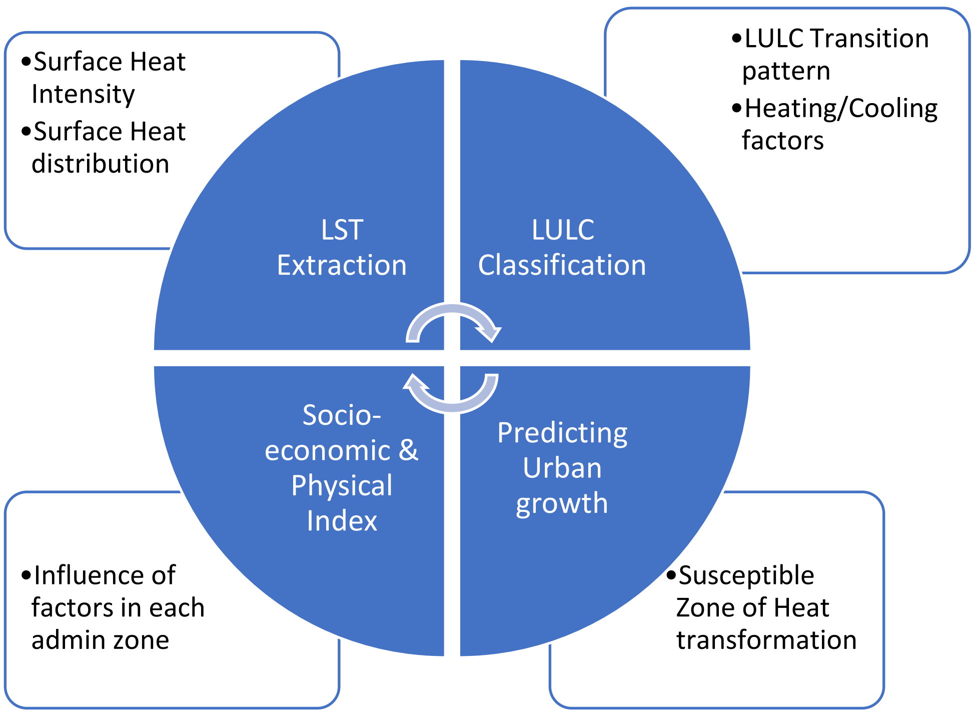


Figure 6: (a) Conceptual and (b) Technical Framework

4.3. **Data and Information**

The study deals with transition information of LULC classes. To investigate further detail of LULC effect on changing of surface temperature, relevant physical and socio-economic data is required as a factor of Landuse transition. Physical and socio-economic variables describe the LULC characteristics while LST is used as a reference variable to represent surface urban heat island effect for the city. Table 3 describes required data and information for the study.

Information	Data	Data Source	Description
Climatic	Land Surface Temperature (LST)	Landsat Satellite	Representative layer of surface thermal properties
Physical	Building	GIS vector data of RAJUK	Total volume of building (height x width)
	Vegetation	Landsat Satellite	Density of vegetation
	Waterbody	Landsat Satellite	Proportion of water area coverage
	Building Geometry	GIS vector data of RAJUK	Building geometric formation releasing or blocking thermal energy emission to or from atmosphere
	Landcover	Landsat Satellite	Broad category Landcover types
	Landuse	GIS vector data of RAJUK	Detail Landuse classification types
Socio-economic	Population Density and Growth Rate	Bangladesh Bureau of Statistics	Total population density and growth rate at 10 years interval as per area

			of statistical administrative unit
	Community Facilities	Bangladesh Bureau of Statistics	Number of different types of community facilities located within area of statistical administrative unit
	Affordable Household (HH)	Bangladesh Bureau of Statistics	Portion of affordable HH in terms of building types (permanent structure), located within statistical administrative unit
	Household (HH) with Electricity Connection	Bangladesh Bureau of Statistics	Portion of total HH with accessibility to electricity, located within statistical administrative unit
	Household (HH) size	Bangladesh Bureau of Statistics	Average size of total Households located within statistical administrative unit

Table 3: Data and Information

4.4. Means of Measurement

4.4.1. Climate

Land Surface Temperature (LST) is the climatic variable used as a reference indicator of surface urban thermal property. Pixel based absolute LST value has been used as SUHI indicator of the area distributed within the administrative boundary of the city. The reason behind selecting absolute LST value is to compare direct effect of Landuse change on surface. Table 4 describes climate variable properties which is considered as a reference variable for the study.

SL	Variable	Parameter	Indicator	Unit of Measurement
1	LST	Surface Heat Intensity	LST is used for direct indicator Surface Urban Heat Island (SUHI) effect	Mean of NLST at 30 m spatial resolution located within Thana boundary

Table 4: Climate Variable (Source: Shastri & Ghosh, 2019; Rizwan et. al., 2008; Zhao et al. 2014)

4.4.2. Socio-economic

Socio-economic factor deals with the effect of anthropogenic activity. Level of energy consumption increase the level of emission and therefore information about building material and electricity consumption indicated the rate of heat emission at household unit level of different income group. Apart from these population density, growth rate and HH size are other relevant socio-economic variable to be measured based on given information in Table 5.

SL	Variable	Parameter	Indicator	Unit of Measurement
1	Decadal Growth Rate	Trend of Population Growth	LST increases with an increase of decadal growth rate	Population growth rate at every 10 years in a Thana
	Population Density	Size of Population per Unit Area	LST increases with an increase of population density	Population density per sq km of Thana area
	Density of community facilities	Number of Education, Health, Social and Religious Institutions per unit area	Concentration of community facilities influence surface heat by commuting population	Counts of community facility in each Thana
	Percentage (%) of Affordable	Level of Land Consumption by Building Type	Affordable and non-affordable HH has	Percentage of affordable HH

	Household (HH)		varying level of land and resource consumption. The category of affordability has been determined by type of building structure. Permanent structure is considered as affordable while other are non-affordable HH	living in respective Thana
	Percentage (%) of Household (HH) with electricity connection	Level of Energy Consumption by HH Unit	The HH uses electricity implies more consumption of resources. The electricity connected HH have possibility to release more heat in the area	Percentage of electricity connected HH living in respective Thana
	Average Household (HH) size	Proportion of area usage by each HH	Higher HH size indicates less per capita consumption of existing facility and resources within respective Thana	Mean of HH size located within respective Thana

Table 5: Socio-economic variables (Source: Parsaee et. al., 2019; Magli et.al, 2015; Jusuf et al., 2007; Shahmohamadi et al., 2010)

4.4.3. **Physical**

The principles of selecting physical factor in this research is to consider heat storage flux by physical attribute of a certain area. Building volume is the indicator of total amount of heat absorption whereas sky view factor delineates the amount of heat block as determined by building geometry. Other than building footprint, the building shadow also affects the heat flux within the region. Water and vegetation features allow solar heat to be converted into latent heat through the process of evaporation and evapotranspiration, resulting an increase in cooling effect. Table 6 illustrates the detail about parameters, indicator and unit of measurement of each physical variable.

SL	Variable	Parameter	Indicator	Unit of measurement
1	Building Density	Volume (3D) of Building Coverage	Higher volume of building surface absorbs	Density of building volume (height x

			more short-wave solar radiation and release higher long wave radiation after sunset	width) within per sq km Thana area
	Waterbody Density	Area Coverage by Waterbody	Because of latent heat properties, areas of higher waterbody density have less exposure to surface heat	Density of waterbody area within per sq km Thana area
	Vegetation Density	Normalized Differential Vegetation Index	Because of latent heat properties, areas of higher vegetation density have less exposure to surface heat	Total value of NDVI within per sq km Thana area. Because of NDVI value range between -1 to +1, the sum of total NDVI pixels is considered as indicator located in Thana boundary
	Sky View Factor (SVF)	Level Openness to Sky from ground	If buildings in a area is situated sparsely, the longwave emitted radiation from surface uninterruptedly goes back to atmosphere and hence causes less surface temperature increase	Mean pixel value of SVF at 2 m spatial resolution in respective Thana
	Percentage of Shadow Area	Area coverage of Shadow by building	The coverage of shadow causes inaccessibility of solar short-wave radiation to the shaded area. although it has a cooling effect at micro scale but might indirectly increase surface temperature because of sources of shadow such as building height	Percentage of shadow area out of total Thana area

Table 6: Physical Variables (Source: Oke, et al., 2017; Gunawardena et al., 2017; Dare, 2005)

4.5. **Method**

4.5.1. **LST Retrieval and SUHI Indicator**

LST retrieval is crucial part of this study. Below equation is used to determine LST for all the three-year study (Weng, Lu, & Schubring, 2004).

$$\mathrm{LST} = \frac{T_i}{1 + \left(\lambda \times \frac{T_i}{\rho}\right) \times \ln(\varepsilon)}$$

Here,

LST = Land Surface Temperature, Ti = sensor's brightness temperature, λ = emitted radiance's wavelength, Ɛ = spectral emissivity of the land surface, ρ= hc/σ= 1.438 ×10 − 2 mk, where h and c indicates Plank's constant and velocity of light respectively. σ is the Boltzmann constant. In this process, at first thermal band spectral radiance is converted to actual radiance sensor brightness temperature. The brightness temperature is affected by atmospheric phenomena which is improved using NDVI as emissivity value (Sobrino, Munoz, & Paolini, 2004).

Furthermore, a classification of SUHI magnitude is conducted by normalization of LST pixel values (Weng, Rajasekar, and Xuefei 2011). For normalization minimum and maximum value has been used. On the other hand, for classification mean and standard deviation has been used (Weng et. al., 2019).

$$\mathrm{NLST_i} = \frac{\mathrm{LST_i} - \mathrm{LST_{min}}}{\mathrm{LST_{max}} - \mathrm{LST_{min}}}$$

4.5.2. **Landuse Landcover Classification**

Landcover classification follows Anderson level I classification system dividing the city into four LULC classes such as Built-up, Vegetation, Waterbody and Baren land (Anderson et. al., 1976). The detail description of LULC classes has been given in Table 7.

SL	Landuse Landcover class	Description
1	Built-up area	All types of manmade structures: residential, industrial, commercial and services; transportation and utilities; mixed urban or built-up
2	Waterbody	River, permanent open water, lakes, ponds and reservoirs; Permanent and seasonal wetlands, marshy land, rills and gully, swamps
3	Vegetation	Deciduous forest, mixed forest lands, palms, conifer, scrub and others Crop fields, fallow lands and vegetable lands
4	Bare land	Exposed soils, sand fill, landfill sites, and areas of active excavation

Table 7: Description of Landuse Landcover Class (Mamun, A. A.Mahmood, A. and Rahman, M., 2013)

To extract spatio-temporal base information of LULC into mentioned classes, three different period of temporal image data at 10 years interval in 2001, 2011 and 2021 have been has categorized. These specific years have been chosen to align with yearly statistical census information of the city corporation by Bangladesh Bureau of Statistics (BBS). For Landcover data extraction unsupervised classification technique has been adopted (Oyekola & Adewuyo, 2018). The image classification has been conducted using the ISODATA clustering method. Through this method the image has been categorized into pixel-based classes and distinctive LULC classes have been distinguished. This process further leads to a thematic raster layer using the in-built ISODATA algorithm of ERDAS Imagine software. Maximum number of iterations set to 20. The pixels were identified for desired four land categories on the basis of shape, size, texture, tone and pattern of group of pixels. To remove confusion, Google Earth Pro software has been used to cross-check real time information of earth feature as given on the same date of collected Landsat imagery (Table 3). After completion of assigning respective class code for each pixel, finally LULC map has been produced for each year.

Satellite	Sensor	Year of Acquisition	Spatial Resolution	Spectral Band (Wavelength in micrometer)
Landsat 5	Thematic Mapper (TM)	2001	30 m Band 6 - 120 m (Resampled 30 m)	Band 1 - 0.45-0.52 Band 2 - 0.52-0.60 Band 3 - 0.63-0.69 Band 4 - 0.76-0.90 Band 5 - 1.55-1.75 Band 6 - 10.40-12.50

				Band 7 - 2.08-2.35
Landsat 8	Operational Land Imager (OLI)	2011 and 2021	30 m Band 8 - 15 m Band 10 & 11 – 100 m (resampled to 30 m)	Band 1 - Coastal aerosol 0.43-0.45 Band 2 - Blue 0.45-0.51 Band 3 - Green 0.53-0.59 Band 4 - Red 0.64-0.67 Band 5 - Near Infrared (NIR) 0.85-0.88 Band 6 - SWIR 1 1.57-1.65 Band 7 - SWIR 2 2.11-2.29 Band 8 - Panchromatic 0.50-0.68 Band 9 - Cirrus 1.36-1.38 Band 10 – TRIS 10.60-11.19 Band 11 – TRIS 11.50-12.51

Table 8: Satellite data specification (Source: USGS)

4.5.3. LULC Projection

To produce predicted map of LULC for the year of 2031 and 2041, Cellular Automata – Markov (CA-Markov) model has been used (Kafy et. al., 2021). LULC maps of previous years such as 2001 and 2011 have been used as source data (GIS) for the model. The source map data should have same LULC class code, geographic coordinate, spatial resolution, pixel depth, pixel alignment and extent. The parameters for LULC projection are described in Table 9.

SL	Parameter	Description	Justification of assumption
1	Distance from new built-up area	Existing trend and location of built-up class in 2021 LULC class.	The area which is spatially closer to recently developed built-up are more potential for future built-up class.
2	Road	Existing location of major roads	There is more possibility of urban area grows which is closer to major roads
3	Surface Elevation	High and low surface of land	Urban areas tend to be developed on areas with higher surface elevation
4	Slope	Flat and uneven surface	The possibility of built-up growth higher in comparatively flat land.

5	Transition sub-model	Pattern of Transition from other(waterbody/vegetation/bare land) to built-up class	The spatial pattern of built-up growth will follow the same trend of growth as occurred in previous years unless major intervention takes place.

Table 9: LULC Projection parameters

Using the input parameters, the predicted LULC map has been generated for the year of 2031 and 2041. Before generating prediction map, the model validation has been checked using transition sub model. Transition sub-model map shows all the sub-model parameters such as waterbody to built-up, vegetation to built-up and bare land to built-up hits accurately in predicted pixels of model. The model learning accuracy varies between 36% to 42% across all the steps. Thus, the pixel hits for transition sub-models and learning accuracy statistics shows the acceptable level of accuracy.

4.5.4. Socio-economic and Physical Index

Socio-economic and physical index of respective Thana has been calculated using existing parameter value and weight of each variable of both factors. Below equation has been used to calculate index (Larsson, 2000).

Index of Factors, $F = \sum (W_i \times V_i)$ ……………………….. (i)

Here,

W_i = Weight of Variable i and V_i = Value of Variable i

Weight has been determined by concentration ratio of correlation between mean NLST change and all the variables of socio-economic & physical factors within respective Thana. Thus, index of each variables considers strength of relationship of each variable with heat increasing intensity. however, the calculation of weight does not consider the type of relationship (positive and negative correlation).

$W_i = C_i / T_c$ …………………… (ii)

Here,

(Ci = Correlation value between variable i and mean NLST change and Tc = Total of correlation values of all variables

As the variables of factors belong to different scale and unit of measurement. Therefore, it is necessary to standardize the values into certain range to measure the level of influence at a common scale. The maximum and minimum value of respective variables have been considered as the range of influence by individual feature located within the boundary of study area. For this study a range between 1 to 100 has been considered and all the different variables have been rescaled using below equation (Han et. al., 2012)

$$v'_i = \frac{v_i - min_A}{max_A - min_A}(new\_max_A - new\_min_A) + new\_min_A. \qquad \text{...........(iii)}$$

Here,

v'i = Transformed value, vi = Input, minA = minimum vakue of original dataset, maxA = maximum value of original dataset,new_ minA = minimum value of transformed dataset, maxA = maximum value of transformed dataset.

Although minimum maximum standardization technique performs a linear transformation of original values of variables, but it preserves the relationship among original data values (Han et. al., 2012).

Using the equation (ii) and (iii), Index of socio-economic and physical factors has been calculated as per equation (i). For calculating index, only sum of respective variables of individual factors has been considered, however, weight measurement by concentration ratio considers sum of all the variables irrespective of factors. By such measurement of weight, total effect of surface heat increase has been considered collectively for a particular Thana boundary.

4.5.5. **Validation and LULC Accuracy Assessment**

Validity and accuracy of satellite derived output on surface temperature and classes is necessary to state the reliability of extracted base information. In this study multispectral and thermal band data of Landsat satellite sensor has been used to classify LULC and to extract LST. As the study has limitation of collecting in-situ measurement about surface and air temperature, therefore the process of validation of temperature data depends on the given results of secondary sources such as findings from relevant research papers. On the other hand, for assessing accuracy of satellite derived LULC classes information for three different years of 2001, 2011 and 202, Landuse information has been collected from existing Landuse GIS data and google earth image and accuracy result produced using error matrix. Furthermore, to assess accuracy of Markov model generated LULC prediction map for the year of 2031 and 2041, existing classified LULC map and model generate predicted map for the same year of 2021 have been compared.

4.5.5.1. *LST Validation*

Regarding validation of LST in accordance with the value collected from in-situ measurement, a study conducted by Rigo and other (2006) shows satellite derived long wave upward radiation of Landsat has a bias of 1.9 Kelvin and RMSE of 1.2 Kelvin. Although, the temperature result finds a better correlation for NOAA-AVHRR and MODIS sensor, but due to highest spatial resolution of Landsat product has been used in this study. Sharma and Joshi (2014) also find in their study a high degree of agreement between the satellite retrieved surface temperature and the ground based LST observations. As per result of the study, the correlation, root mean square (RMS) different and standard deviation for two sets of data is estimated as 0.89, 0.5 °C and approximately 0.72 °C respectively. On another study by Yuan and Bauer (2006) also states the similar pattern satellite derived LST value compared to ground measured surface temperature across 13 stations. As stated in both studies, based on such linear relationship between satellite and ground observation, Satellite extracted LST value is considered as a well representative parameter for measuring surface heat intensity and used in many study (Mallick et. al., 2013). Moreover, Gawuc and others (2022) states in their research there is a linear relationship between atmospheric and surface urban heat island. Considering the outcome of findings, the use of satellite derived LST can be considered as well justified proxy indicator for surface urban heat intensity and represents a linearity with atmospheric urban heat island.

4.5.5.2. *Accuracy of LULC Classification*

To calculate accuracy of unsupervised and predicted LULC classification result, error matrix tool has been used (Kafy et. al., 2021). A number of randomly selected 200 points have taken as sample to cross check its overlaying LULC class attribute. A minimum number of 40 samples has been taken from each LULC classes such as built-up, waterbody, vegetation and bare land. For unsupervised classification LULC maps, the sample points have been collected from google earth images of respective years and cross-checked for the year of 2001, 2011 and 2021. Whereas, for predicted LULC maps generated by Markov model, the same number of sample points have been crossed checked between existing (unsupervised classification) and predicted (Markov model generated) maps for the same year of 2021. The matrix gives result of overall accuracy, user accuracy, producer accuracy and kappa coefficient. A 70% value is acceptable, while a range of 0.40 and 0.85 is considered as acceptable for Kappa Coefficient (Basu & Das, 2021).

$$\text{Overall accuracy} = \frac{\text{Total number of corrected classified pixels (diagonal)}}{\text{total number of reference pixels}} * 100$$

$$\text{User Accuracy} = \frac{\text{number of correctly classified pixels in each catagory (diagonal)}}{\text{total number of reference pixels in each category (row total)}} * 100$$

$$\text{Producer Accuracy} = \frac{\text{number of correctly classified pixelxs in each category (diagonal)}}{\text{total number of reference pixels in each category (column total)}} * 100$$

$$\text{Kappa Coefficient (T)} = \frac{\text{Total number of Sample*Total Number of Corrected Sample} - \sum \text{(col.tot*row tot)}}{(\text{Total number of Sample})^2 - \sum \text{(col.tot*row tot)}} * 100$$

Workflow Diagram

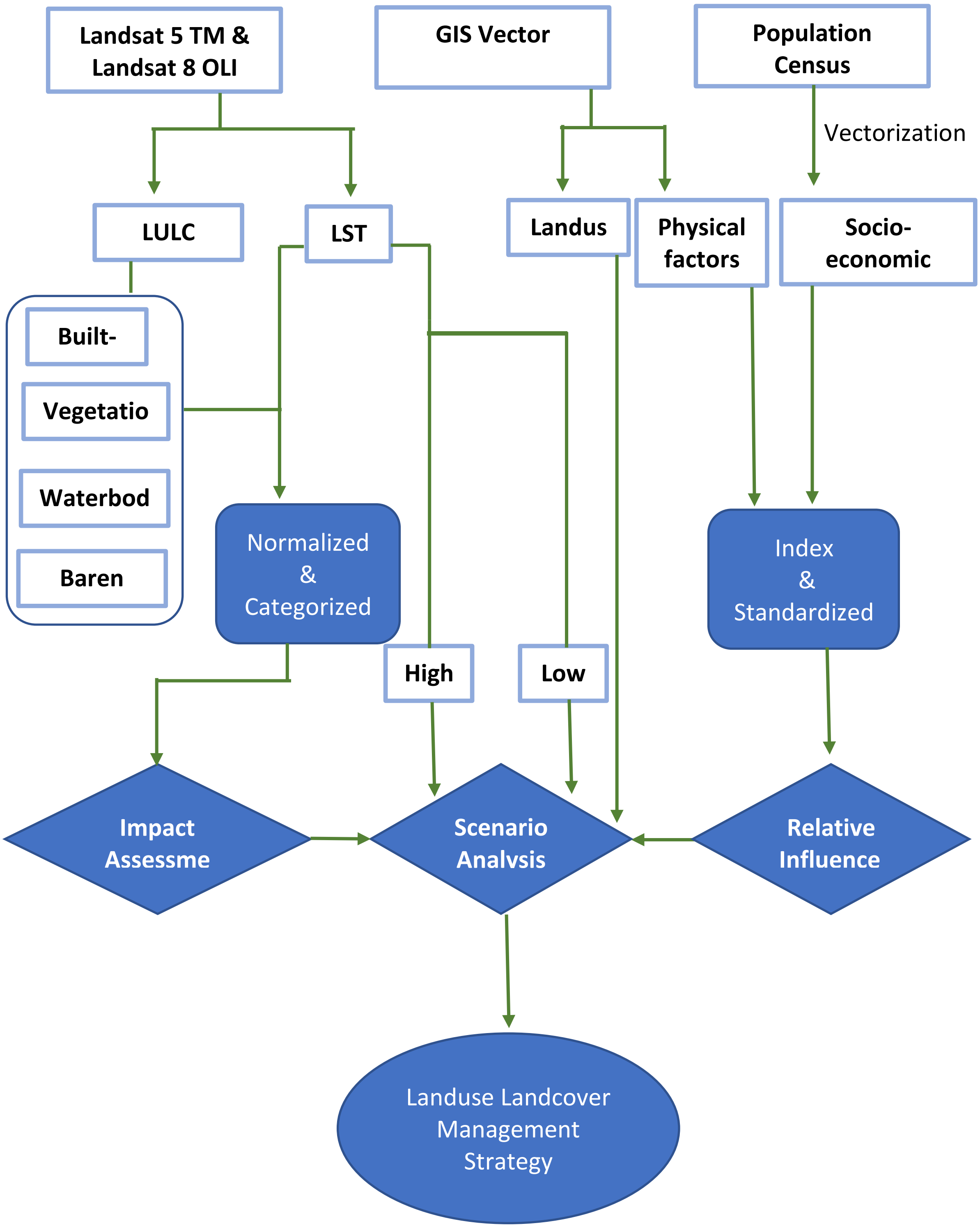


Figure 7: Workflow Diagram

CHAPTER 5: ANALYSIS AND FINDINGS

5.1. Introduction

This chapter depicts the analytical results of information processed from different data sources. The chapter is divided into three parts. The first part describes Landuse Landcover (LULC) transition scenario and its implication with Surface Urban Heat Island (SUHI) increase over the period. Second part discusses about how different types of factors are combinedly affecting SUHI variation in different administrative zones across the study area. Final part of this chapter finds the areas of future LULC transition pattern potential to cause high heat increase.

5.2. LULC Transition

The pattern of LULC transition clearly states a significant increase in built-up and decrease in waterbody, vegetation and built-up over the period. Although, there is a continuous decrease in all other landcover class except vegetation. Vegetation shows an increase in 2011 but dramatic decrease in 2021. Nonetheless, the area percentage of vegetation class in 2021 is less than that of in 2001. Figure 8 and Figure 9 presents the LULC map of 2001, 2011 and 2021 and trend of LULC changes. Table 10 indicates accuracy assessment result using the error matrices formula. The percentage value of user accuracy, producer accuracy, overall accuracy and Kappa coefficient shows the classification of LULC meets the accepted range of percentage in each category.

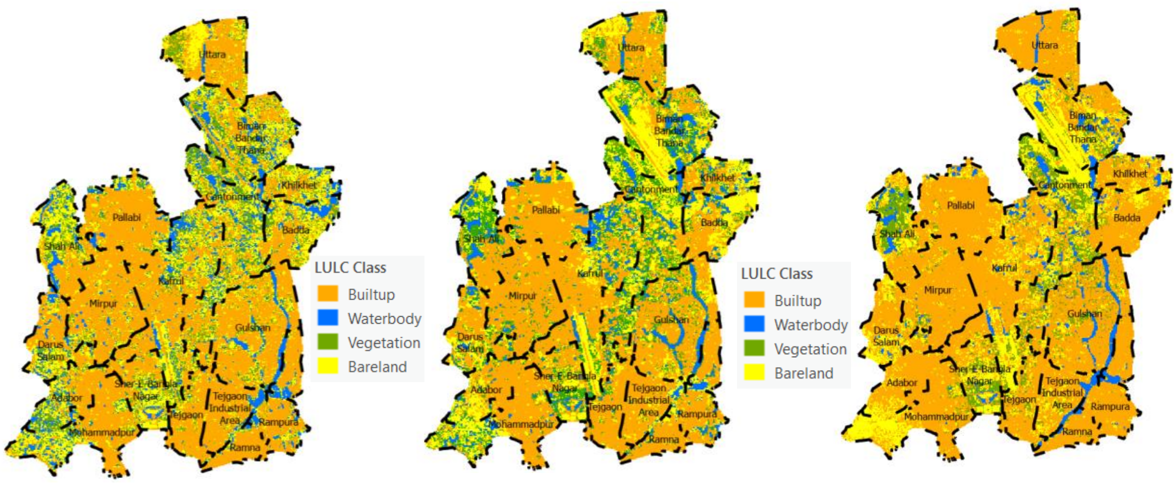


Figure 8: Map of LULC class of 2001, 2011, 2021

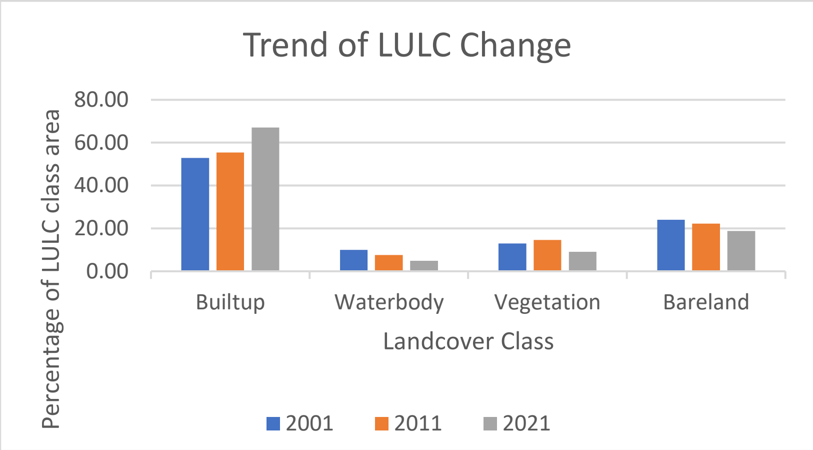


Figure 9: Trend of LULC changes in area percentage of 2001, 2011, 2021

Year	User Accuracy				Producer Accuracy				Overall Accuracy	Kappa Coefficient
	Built-up	Water body	Vegetation	Bare land	Built-up	Water body	Vegetation	Bare land		
2001	91.23	89.67	85.79	86.4	90.65	88.16	82.21	87.43	94.32	0.956
2011	93.87	90.43	81.82	83.33	92.53	91.56	84.69	88.96	91.19	0.904
2021	92.18	87.91	86.51	91.74	89.38	90.41	81.32	84.17	92.64	0.923

Table 10: Accuracy result of LULC Classification

Table 11 describes different statistics of LULC classification result. According to the result, the overall growth of built-up area from 2001 to 2021 is 21.13% with a decadal increase of 4.70% and 21.10% during 2011 and 2021 respectively. Over the analysis period, waterbody has the highest rate of decrease with an overall rate of change of -103.63%, along with continuous decadal decrease rate of 23.69% and 35.65% respectively for the year of 2011 and 2021. Bare land follows the same pattern of decrease having a double decadal change rate in later year than earlier. However, only vegetation shows different pattern of change in the intermediate year of 2011 with a 12.78% increase decadal change, which fell to -37.77% decreasing change rate during 2021. However, there is rapid fall in the percentage on following decade with -42.49%.

LULC Class	Area in hectares			Percentage of area			Decadal Rate of Change		Overall Rate of Change
	2001	2011	2021	2001	2011	2021	2011	2021	2001-2021
Built-up	**5049.72**	**5287.14**	**6402.87**	**52.96**	**55.45**	**67.15**	**4.70**	**21.10**	**21.13**
Waterbody	**958.14**	**731.16**	**470.52**	**10.05**	**7.67**	**4.93**	**-23.69**	**-35.65**	**-103.63**
Vegetation	**1234.80**	**1392.66**	**866.61**	**12.95**	**14.60**	**9.09**	**12.78**	**-37.77**	**-42.49**
Bare land	**2292.93**	**2124.63**	**1795.59**	**24.05**	**22.28**	**18.83**	**-7.34**	**-15.49**	**-27.70**
Total	**9535.59**	**9535.59**	**9535.59**	**100**	**100**	**100**	**-**	**-**	**-**

Table 11: Statistics of LULC changes during 2001 to 2021

5.3. SUHI Intensity and Distribution

Normalized Land Surface Temperature (NLST) map result shows a lion's share of total study area has been experiencing increasing pattern of surface heat since 2001. The amount of land where heat has increased covers 87.39% of total area. Rest of the major part has a decreasing trend accounting for 12.38% and a small percentage remains stable within the area of Dhaka North City Corporation (Figure 10).

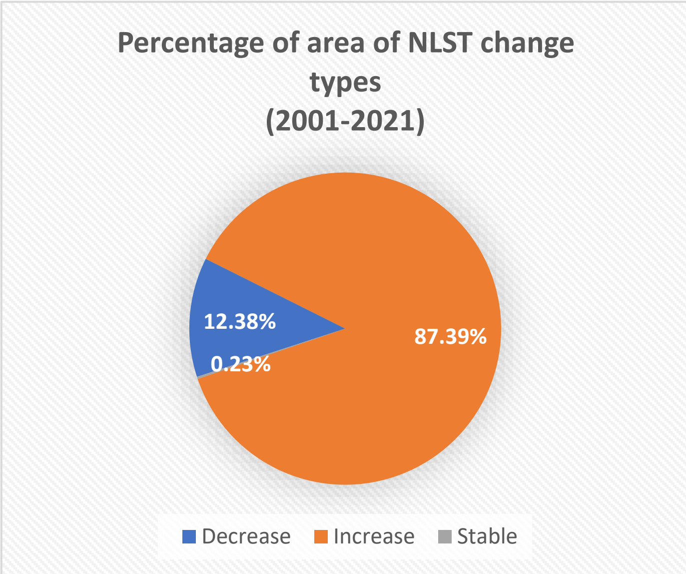


Figure 10: Change of NLST area in percentage during 2001 to 2021

Going into detail of 87.39% heat increasing area, it is found that majority percentage falls under the category of low increase of surface heat with a percentage of 85% out of total areas where heat has increased (Figure 11). The rest 15% is divided into moderate increase (14%) and high increase (1%), which defines a zone of highest surface heat prevalence across the study area. This 15% of total heat increased areas can be simplified as the areas of HI-moderate heat increase zone. This study investigates the LULC transition pattern within these Hi-moderate areas to understand what type of changes in LULC class contributes to the maximum increase level of surface heat. Figure 12 presents Map of different types of surface heat change during 2021 to 2001 in the urban area of Dhaka North City Corporation. The percentage of overlayed existing Landuse data shows that residential usage of land is prominent and accounts for 38% of total

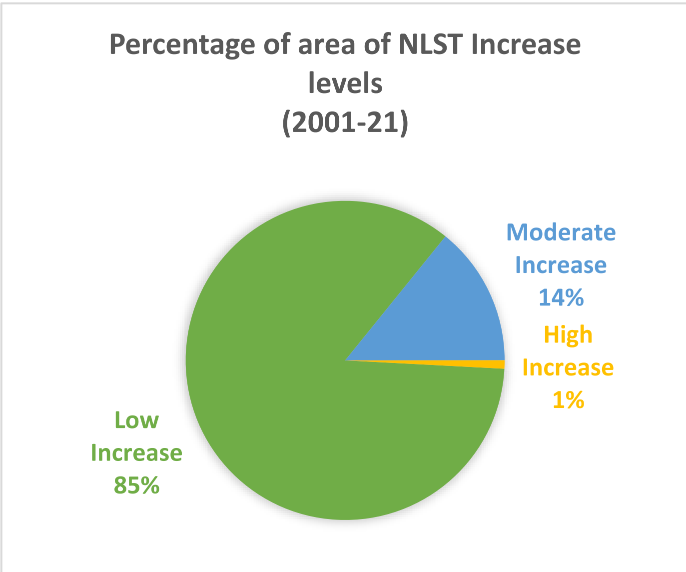


Figure 11: Change of NLST increased types in area percentage during 2001 to 2021

Hi-moderate heat increase zone, followed by mixed use (15%), vacant (14%) & transport (12%) Landuse types respectively (Figure 13).

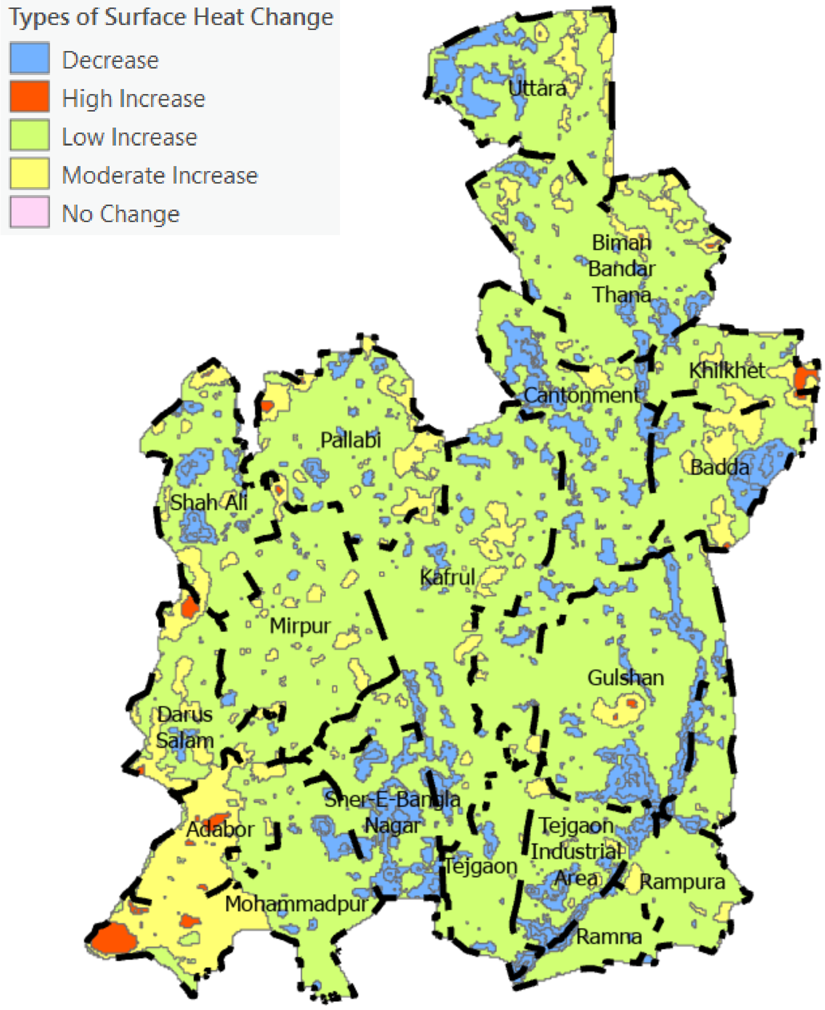


Figure 12: Map of different types of surface heat changes from 2001 to 2021

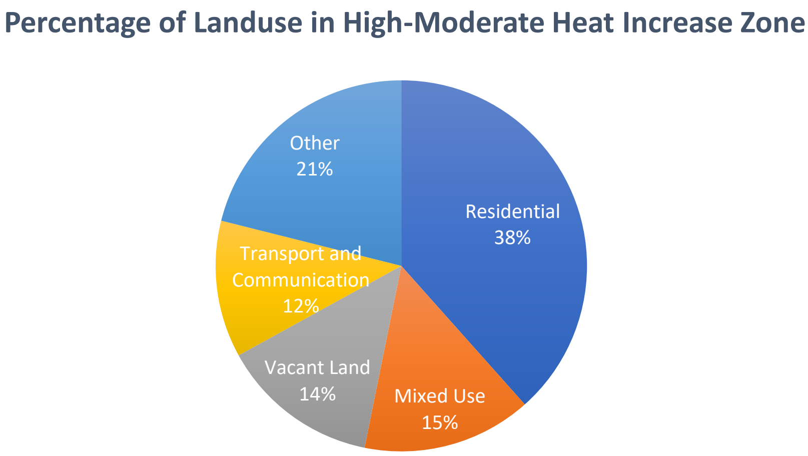


Figure 13: Percentage of area of existing Landuse within Hi-moderate Heat Increase zone

5.4. Pattern of LULC transition in High-moderate increase zone

From the decadal analysis of land transformation in the year of 2001, 2011 and 2021, the pattern of LULC transition has been identified at each unit of 30-meter areal unit of land. A total of 59 types of LULC transition has been identified within the area of High-moderate heat increase. As per result of pearson's correlation, Built-up and Bare land shows a positive correlation whereas waterbody and vegetation are negatively correlated with NLST change (Table 12). Furthermore, there is a consistent pattern of bare land to be converted to built-up class. From spatial information It is found that 2/3 of the bare land in the earlier years of 2001 or 2011 had been transformed into built-up in the later year of 2021 (Figure 14). The map shows peripheral areas like Uttara, Badda, Khilkhet and Adabor will have higher concentration such transformation, although the transformation will happen al across the study area at different level.

	NLST	Built-up	Waterbody	Vegetation	Bare land
NLST	1				
Built-up	0.43115	1			
Waterbody	-0.41864	-0.61633	1		
Vegetation	-0.57533	-0.72987	0.572954987	1	
Bare land	0.072241	-0.56703	-0.097875998	-0.071888648	1

Table 12: Result of pearson's correlation between NLST change and LULC classes of 2021

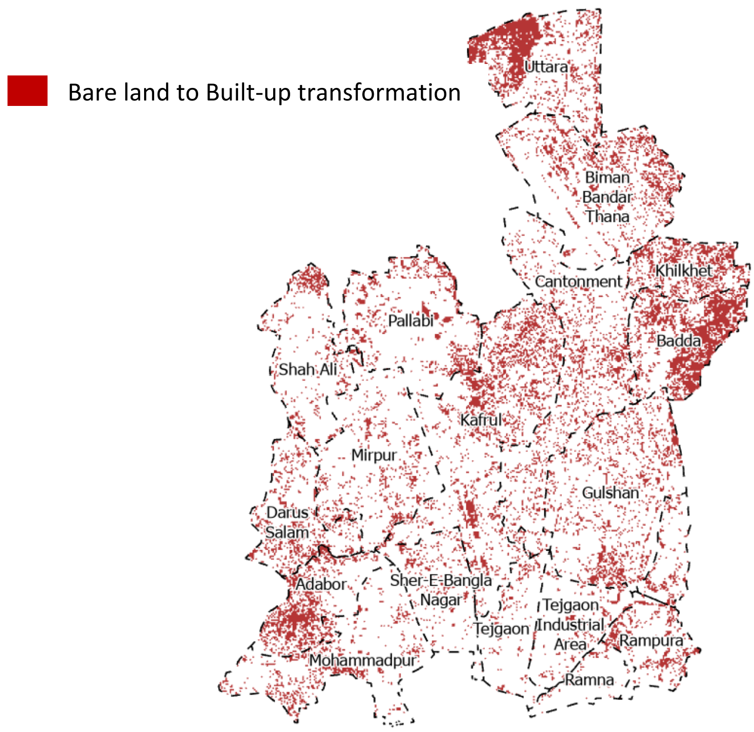


Figure 14: Areas of land transformation from bare land to built-up during 2001 and 2021

Based on above discussed LULC-NLST correlation type and transforming pattern between built-up and bare land classes, below assumption can be made:

a) Built-up and Bare land can be considered as a unique set of LULC class in terms of being positive factor for increasing heat intensity.
b) Waterbody and Vegetation can be considered as a unique set LULC class in terms of negative factor for increasing heat intensity.
c) Bare land has high potentiality to be converted into built-up in following decade and hence can be considered as similar effect in increasing heat intensity.

Based on above statements, the three decadal LULC transition types has been merged and simplified into three categories of transition potentials as given as below in Table 15.

Transition Category	**Phases of Built-up transition**			**Description**
	2001	**2011**	**2021**	
1st Order Urban	Built-up/Bare	Built-up/Bare	Built-up/Bare	Areas with consistent built-up form since earliest year (2001)
2nd Order Urban	Vegetation/Waterbody	Built-up/Bare	Built-up/Bare	Areas with consistent built-up since intermediated year (2011), which used to be vegetation/waterbody in earliest year (2001)
3rd Order Urban	Vegetation/Waterbody	Vegetation/Waterbody	Built-up/Bare	Areas with newly built-up form in the latest year (2021), which used to be vegetation/waterbody in the earliest (2001) and intermediate (2001) years
Other	Any	Any	Any	Areas with other random combination and not associated with chronological order of bult-up formation

Figure 15: Category and Phases of Built-up/Bare land transition from 2001 to 2021

Table 13 describes the contribution of above three order of built-up area formation in increasing heat intensity. The statistics shows 1st Order Urban transition has the highest percentage of land occupied within the geographical range of Hi-moderate Heat increase zone. That means areas which are occupied by mainly built-up types consistently over the three decades has higher influence in increasing surface heat. Similarly, the areas where built-up areas formed subsequently during both decades of 2011 and 2021, shows a descending order of area coverage within the High-moderate heat increase zone. From the findings it can be said that there is a positive relation of heat intensity with the duration of built-up area occupancy. If an area is developed with built-up/bare formation for long periods of time, the area is highly susceptible to heat increase.

SL	Transition category	Area in SQ km	Percentage
1	1st Order Urban	6.69	53.51
2	2nd Order Urban	2.59	20.68
3	3rd Order Urban	1.49	11.92
4	Other	1.74	13.89
	Total	**12.50**	**100**

Table 13: Area occupancy by major LULC transition types in Hi-moderate heat increased zone

5.5. Relate improvement of socio-economic and physical factors on Heat intensity

The analysis in previous chapter illustrates types and effect of urban area transition on increasing pattern of surface heat in city scale. But there is variation of heat intensity in detail scale and it is important to understand the heat characteristics of a smaller areas within the city, which combinedly affect heat intensity and magnitude across the city. Therefore, to investigate the impact of factors and variation on heat intensity in different sub-region within city, a further analysis is necessary on basis of physical and socio-economic condition of respective zones. It is well evident from numerous literatures that, physical factors are triggering the changing pattern of surface heat. A few literatures tried to investigate the effect of socio-economic as well. The result of this section tries to investigate the skewness and level of comparative influence between both factors in increasing SUHI.

5.5.1. Physical and Social Index of the City

A city is dynamic by its physical and social aspect. There is variation in influence of both aspects causing changes in surface heat intensity. In this study, the Dhaka North City Corporation is divided into existing statistical administrative unit known as Thana. Each area has different level of existing physical and social feature, which causes variation in local thermal budget and hence contributing increase of surface heat accordingly.

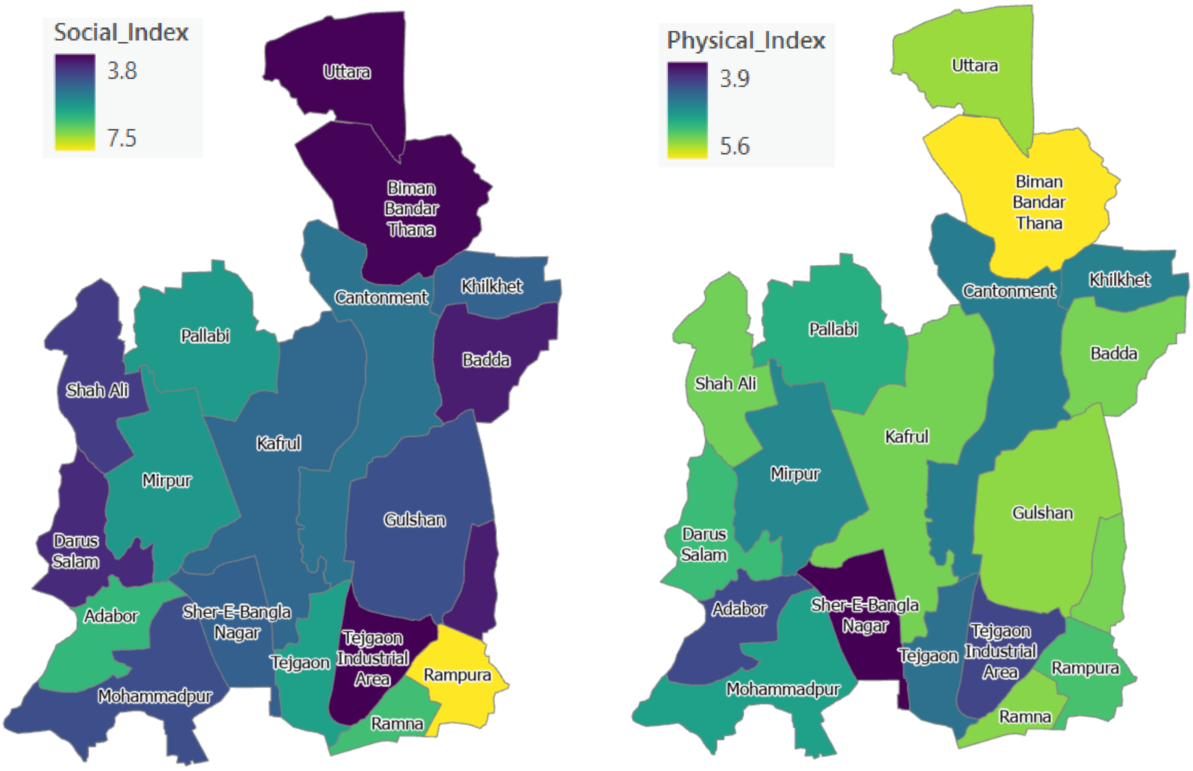


Figure 16: Socio-economic (left) and Physical Index (right) of DNCC

Figure 16 describes distribution of physical and social index according to respective Thana boundary. Social index is higher in Ramna thana, whereas physical properties are prominent in Biman Bandar Thana. On the other hand, the lowest socio-economic and physical index is found in Tejgaon Industrial area and Biman Bandar Thana respectively.

By investigating the spatial distribution pattern using Moran's Autocorrelation, it is found that the city has a random socio-economic and physical pattern. Social and physical attribute of Thana does not belong to any cluster pattern. Furthermore, the Pearson's correlation between index of both factors shows a weak positive correlation (0.18) existing among them. Therefore, the outcome represents that, the city's social and physical structure have neither intra nor inter correlation within and between them respectively, rather both factors are randomly distributed across the city area. As there is no spatial concentration of both type of factor across the area, it is unlikely that any of those have a sole potentiality to intensify heat within a region. So, it is necessary to find the comparative impact of individual factor which contributes most to surface heat change within individual Thana.

5.5.2. **Pattern of influence by factors on surface heat increase**

To assess comparative impact of physical and social factors on surface heat in every Thana, the factors indexes have been further compared with Mean NLST change. Figure 17 represents a Thana wise profile of DNCC including surface temperature increase and intensity of social and physical factors. The bar charts in map show that some areas have higher social index whereas some are physically high. The spatial variation of heat increase is also visible across the city by the size of yellow circles.

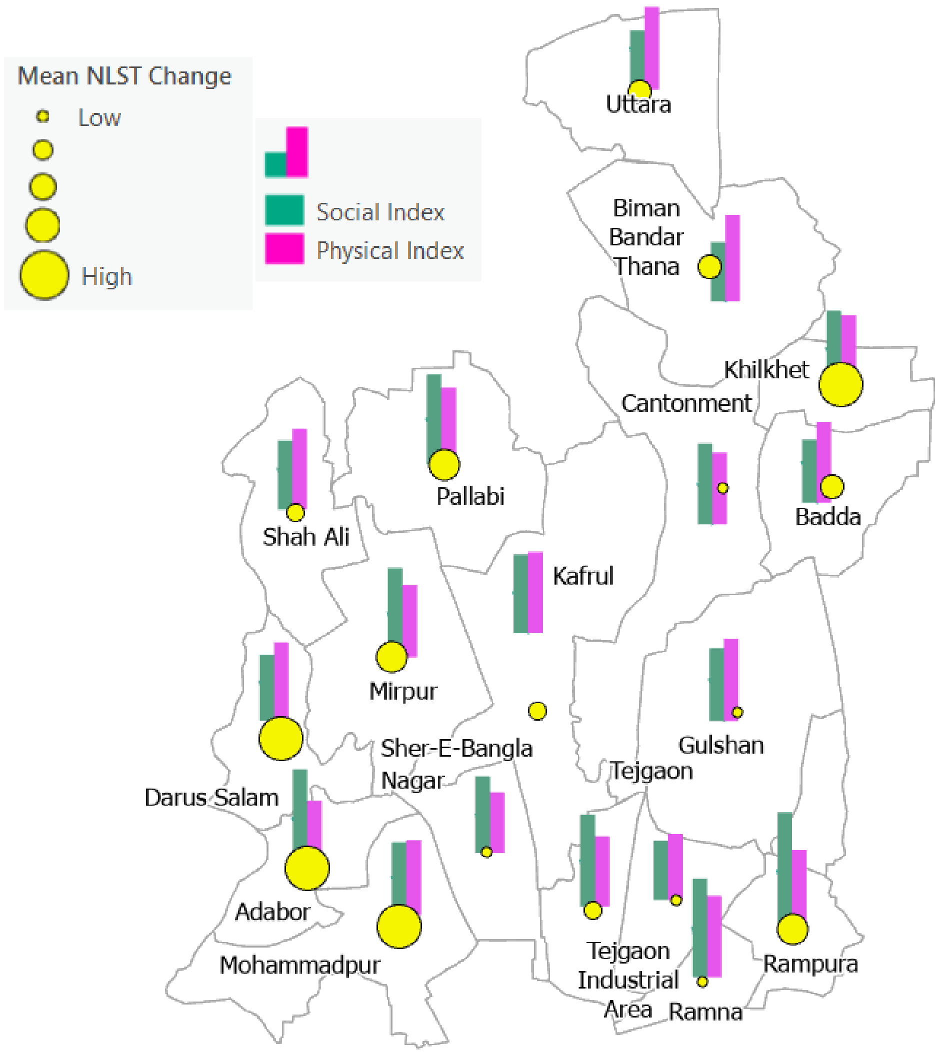


Figure 17: Comparative distribution between Socio-economic and Physical factor in DNCC

The study tries to find a relationship between these three variables to understand how surface temperature is changed by social and physical properties of an area. The scope of this research is to find the pattern of socio-physical influence on the areas on SUHI effect zones. Therefore, it is necessary to consider only those Thana which have evidence of highest increase of surface temperature. To this end, the value of surface temperature increase from 2001 to 2021 years has been classified into quartiles. Table 14 describes index values of social & physical factors and mean NLST change and quartile position of each Thana in scale of 1 to 100. The value of each variable is standardized into the range as to measure the impact of individual variable in a common scale of unit.

SL	Name of Thana	Socio-economic index	Physical index	Mean NLST change	Quartile of mean NLST change
1	**Adabor**	**66.86**	**22.73**	**100.00**	**4th**
2	**Darus Salam**	**12.89**	**68.58**	**63.22**	**4th**
3	**Mohammadpur**	**24.91**	**57.02**	**62.06**	**4th**
4	**Khilkhet**	**32.08**	**44.27**	**61.19**	**4th**
5	Mirpur	53.46	46.95	50.13	3rd
6	Rampura	100.00	71.52	43.02	3rd
7	Pallabi	54.35	62.92	42.89	3rd
8	Biman Bandar Thana	1.96	100.00	40.17	3rd
9	Uttara	1.44	85.47	38.29	3rd
10	Badda	8.86	80.38	37.28	2nd
11	Kafrul	34.14	79.84	31.45	2nd
12	Shah Ali	18.65	78.82	30.77	2nd
13	Tejgaon	57.01	37.52	27.93	2nd
14	Tejgaon Industrial Area	1.00	21.81	19.38	2nd
15	Gulshan	25.06	83.56	17.40	1st
16	Ramna	69.68	82.38	17.11	1st
17	Cantonment	38.35	42.49	16.93	1st
18	Sher-E-Bangla Nagar	31.16	1.00	1.00	1st

Table 14: Social and physical index, mean NLST change and quartiles of mean NLST change

Table 14 shows Adabor, Mohammadpur, Darus-salam and Khilkhet Thana falls in the 4th quartile of mean NLST change value of all the thana. This four Thana represents the top four areas with highest increase of mean NLST from the year of 2001 to 2021. In this study, these four Thana are called Heat Centre Zone (HCZ) of Dhaka North City Corporation because of its presence above 3rd quartile values of mean NLST change. Figure 18 describes the relative influence of socio-economic and physical factor on increasing pattern of surface heat in those Thana experiencing highest mean NLST increase. Of them, Adabor thana has highest level of heat increase over the year having distinct value in the scale and influenced by high level of socio-economic but low level of physical factor. The other Thana namely Darus salam, Mohammadpur and Khilkhet have comparatively lower level of mean NLST increase with a value of 63.22, 62.06, 62.19, under the category of low social-high physical and low social-low physical influence respectively.

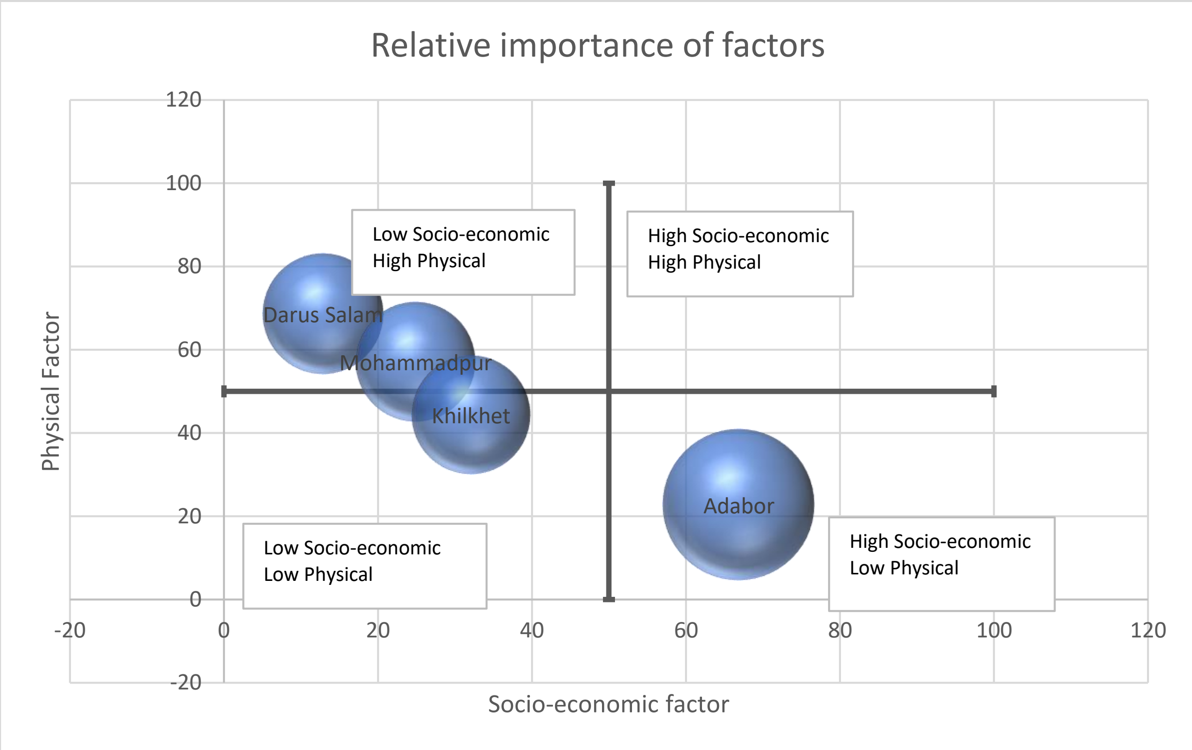


Figure 18: Pattern of influence by Socio-economic & Physical factors in increasing surface heat

Figure 18 also shows the pattern of relative influence of both factors and how surface heat change has decreased with simultaneous decreasing trend of socio-economic factor and increasing trend of physical factor. When an area (Adabor) has high socio-economic index, it shows high increase of heat intensity even after having a lower physical index. The figure also describes those areas with less discrepancy between both factor and gradual decrease from socio-economic factor shows comparatively less intensity of temperature increase. Therefore, the finding suggests a balance between both factors for a particular region. According to quadrant position in figure 18, high socio-economic and low physical index causes increasing pattern of surface heat. Alternatively, the quadrantal position of comparatively lower heat intensified areas also helps to understand that the effect of physical factors is stronger than that of socio-economic in surface heat reduction. Socio-economic variables like population density, density of community facility, percentage of affordable housing determines the rate of land consumption per unit area. For example, a building with same area footprint will have different level of functionality depending on the number of populations using it as well as the type of Landuse. Depending on the level of functionality, an unit of building area will generate varying level of surface heat.

The research further raises the necessity to evaluate the type of effect for each feature or variable under both factors. The correlation output between mean NLST change and underlying variables of both factors reveals that there are two categories of variables such as positive and negative which are playing an important role in increasing and decreasing heat intensity respectively (Table 15 and Table 16). Therefore, it is necessary to address if there is a pattern between positive and negative factors which indicates its contribution for lower heat intensity.

	Mean NLST Change	Decadal Growth Rate	Population Density	Density of Community Facilities	% of Affordable HH	% of HH with Electricity Connection 2011	HH Size2011
Mean NLST Change	1						
Decadal Growth Rate	.542	1					
Population Density	0.292	-0.157	1				
Density of Community Facilities	0.134	-0.413	.562	1			
% of Affordable HH	-0.179	-0.444	0.053	-0.133	1		
% of HH with Electricity Connection 2011	-0.312	-0.286	.490	0.261	-0.358	1	
HH Size2011	-0.388	-.600	0.247	-0.010	.787	0.114	1

Table 15: Correlation result between mean NLST change and variables of Socio-economic factor

	Mean NLST Change	Sum NDVI	Building Density	WB Density	Mean SVF	Percentage Shadow Area
Mean NLST Change	1	-0.087	0.149	-0.138	-0.257	0.248
Sum NDVI	-0.087	1	-.683	0.455	.661	-.610
Building Density	0.149	-.683	1	-.703	-.975	.973
WB Density	-0.138	0.455	-.703	1	.668	-.640
Mean SVF	-0.257	.661	-.975	.668	1	-.986
Percentage Shadow Area	0.248	-.610	.973	-.640	-.986	1

Table 16: Correlation result between mean NLST change and variables of Physical factor

Figure 19 shows influence of positive and negative factors on heat increase of four heat centre zones of Dhaka North City Corporation area. The highest zone (Adabor) of heat increase is skewed towards highest level (100) of positive factor, whereas the contribution of negative factor for the area remains lowest (1) in the scale range of 1-100. The heat change pattern of other comparatively lower heat centre zones describes a gradual decrease in surface heat with increasing influence of negative factors. Therefore, the finding suggests negative factors play key role in reducing the surface heat intensity over time.

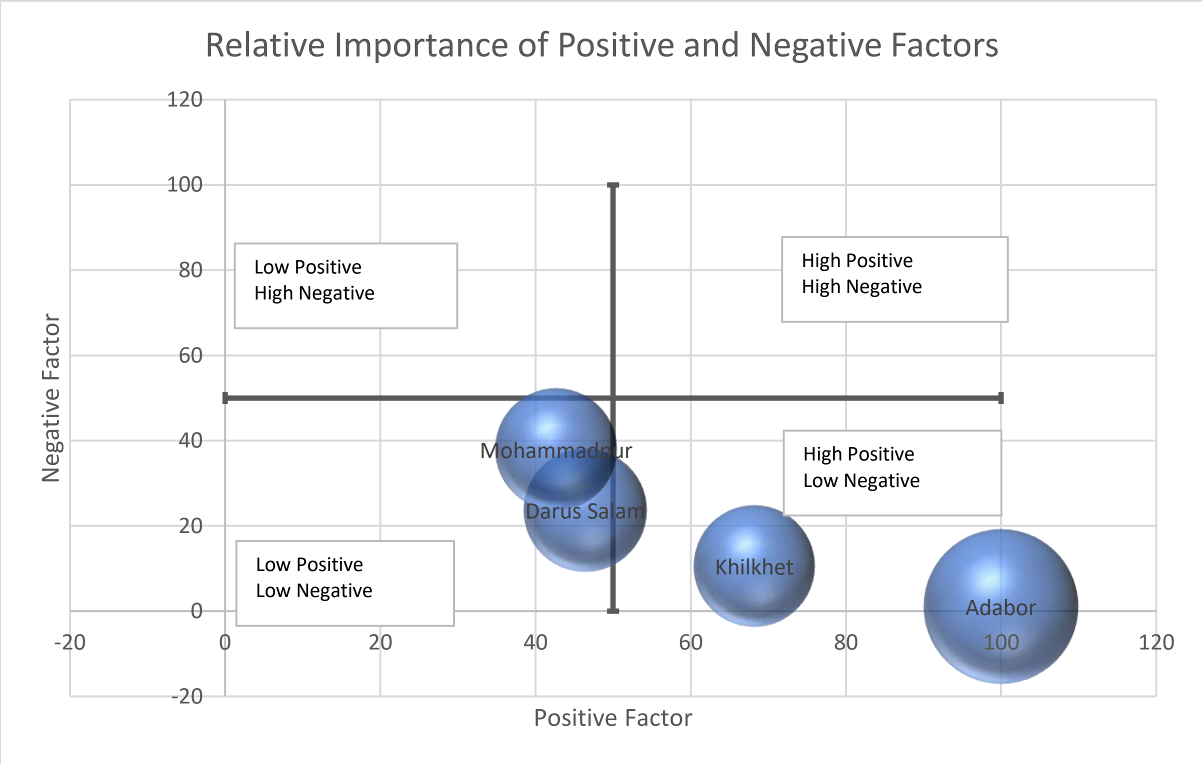


Figure 19 : Pattern of influence by positive & negative factors in increasing surface heat

The study further assesses the possibility of having significant relationship of any variable on heat intensity. Figure 20 and Figure 21 show none of the socio-economic and physical variables remains constantly higher among all the heat centre zones of the city. Moreover, there is no regular trend of index level for both positive and negative variables. So, the output illustrates not any single variable is solely responsible for surface heat increase. rather there is a combined effect by all the variables existing at different magnitude within the zones.

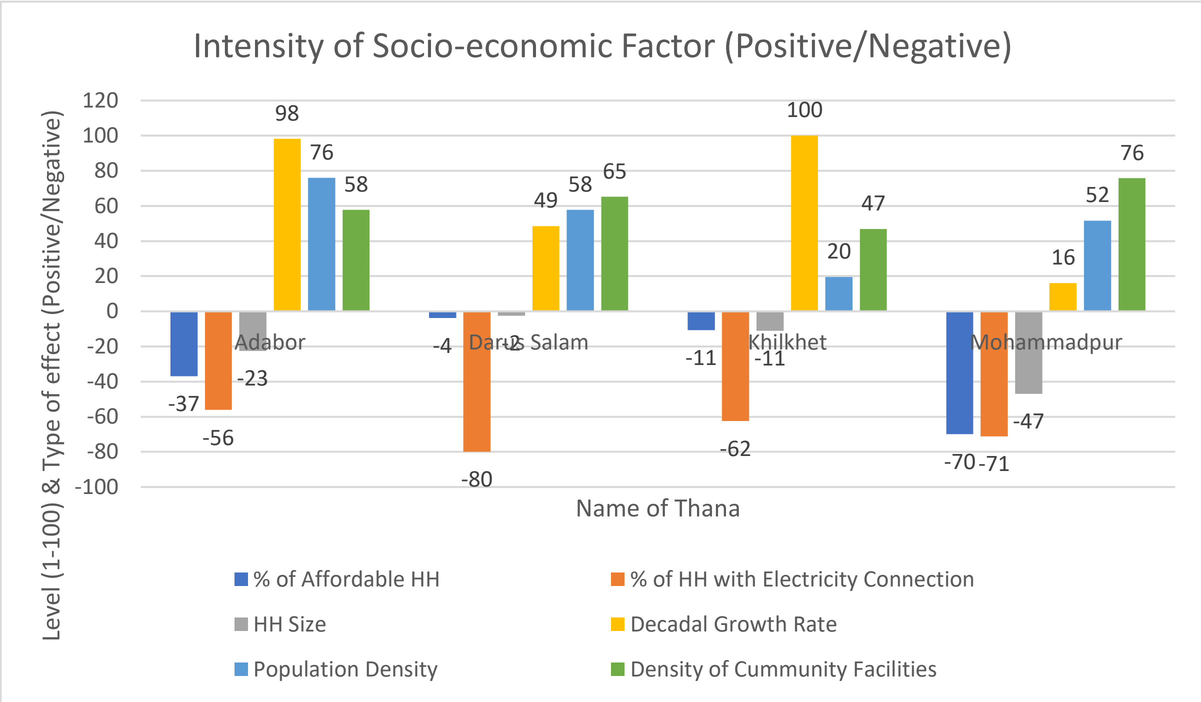


Figure 20: Index of Positive and Negative variables of Socio-economic factor

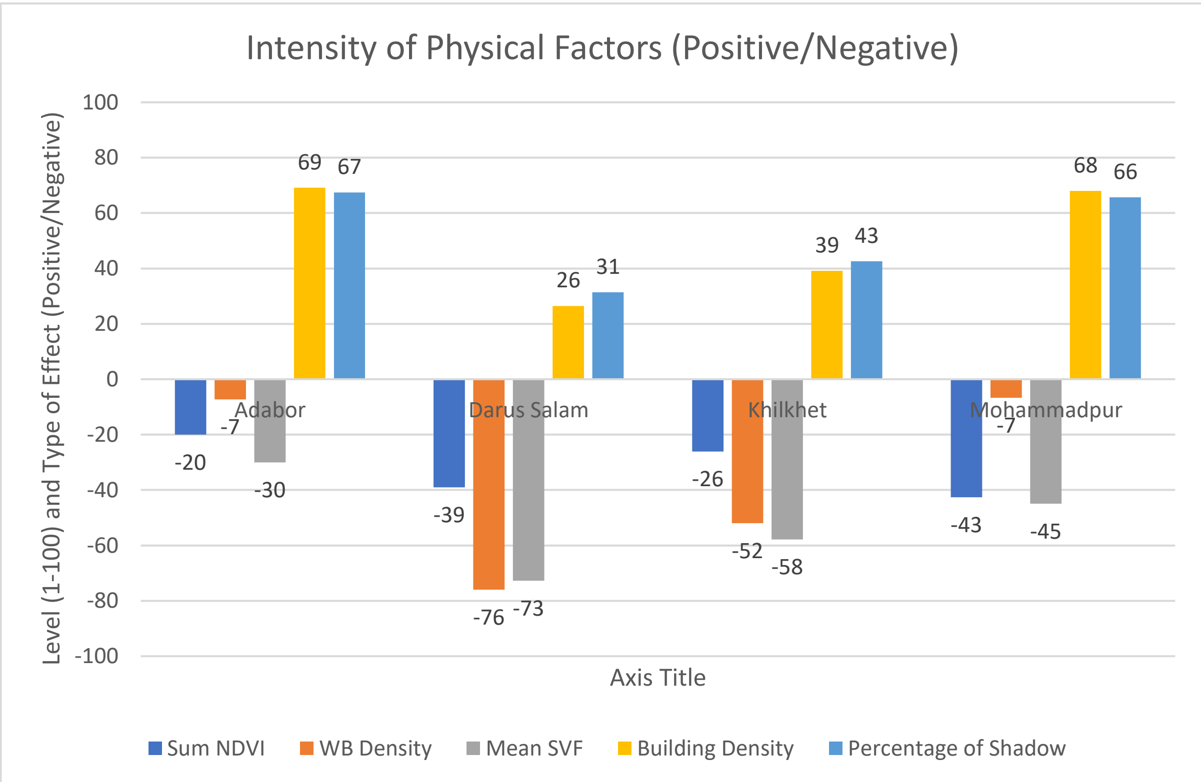


Figure 21: Index of Positive and Negative variables of Physical factor

Finally, this part of analysis can be concluded with such findings that, reduction of heat intensity for a particular area depends on magnitude of physical negative factor located within the region. Although, heat intensity is a result of combined effect by all the relevant variables, however, it is necessary to identify the portion of physical negative variable existing in respective area to minimize the effect of surface urban heat island.

5.6. Urban Growth and Susceptible areas of Surface Heat Increase

To find susceptible areas of heat increase, projection of LULC transition pattern has been analyzed to find which Thana is occupied mostly by either of the transition category as mentioned earlier in Table 4. Using MLP based ANN Markov Chain model of Terrset software, LULC projection has been conducted and future three phases of urban order has been identified for each Thana.

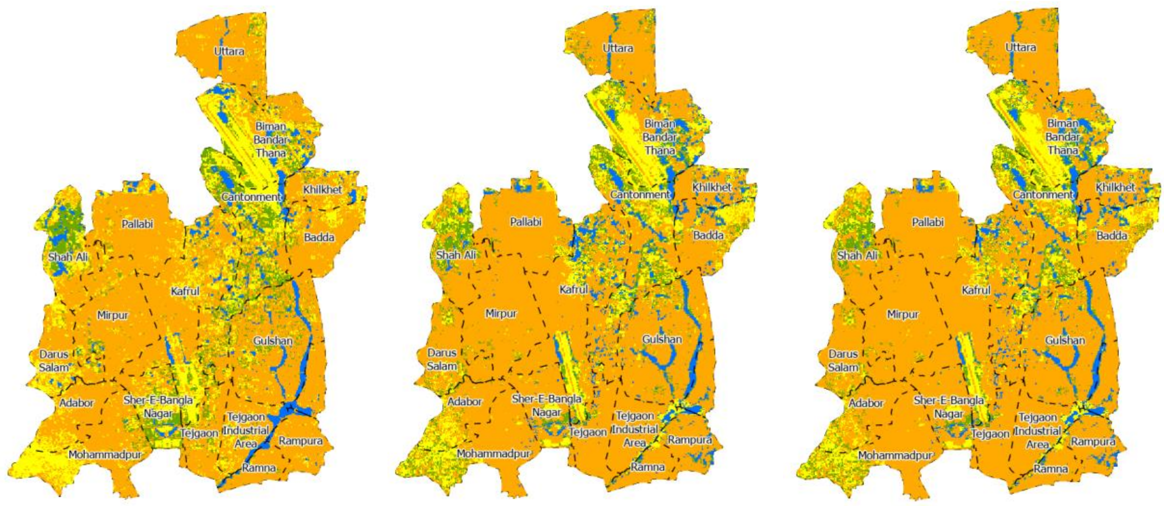


Figure 22: Map of LULC classes of 2021 (existing), 2031 (predicted) & 2041 (predicted)

Figure 22 illustrates LULC of 2021 and predicted LULC for 2031 and 2041. The accuracy assessment of prediction output has been assessed by Terrset software accuracy check and user accuracy matrix. Regarding Terrset assessment, figure 23 shows all parameter setup from other land class to built-up class generates no error. Furthermore, user accuracy results as given in table describes all the land class accuracy

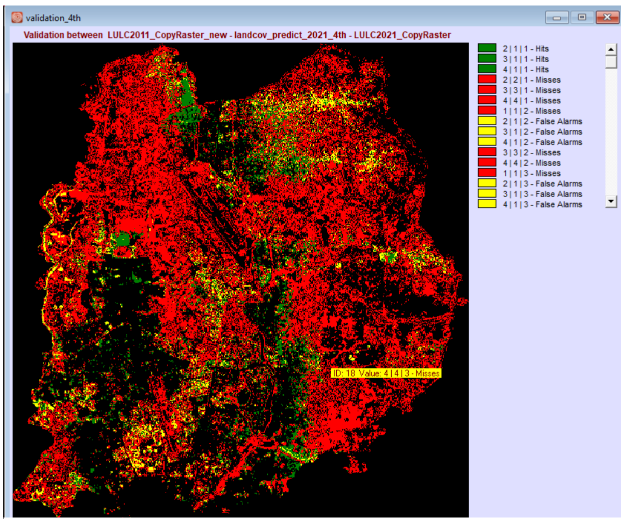


Figure 23: Terrset software generated accuracy result

are above acceptable range of 80. For user accuracy assessment, LULC map of 2021 from projected output and unsupervised classification have been compared. The user accuracy result has been given in Table 17.

LULC Class	Actual area in S1 km	Predicted area in Sq km	Difference	Difference Percentage	Accuracy Percentage
Built-up	101.123	86.1462	-14.9768	-14.81047833	**85.18952**
Water	16.0299	15.3738	-0.6561	-4.092976251	**95.90702**
Vegetation	18.1719	25.7166	7.5447	41.51849834	**81.4815**
Bareland	66.6126	74.7009	8.0883	12.1422974	**87.8577**

Table 17: User accuracy result of LULC projection output

Figure 24 describes an rapid increasing of built-up area while decrease in all other classes. Of total, 72.12 and 75 percent areas within Dhaka North City Corporation will be occupied by built-up class. 85.26% and 86.48% of total area will be combinedly filled up by such land class which triggers surfacce heat intensity during the year of 2031 and 2041 respectively. The statistics shows on an average 86% of total area in each Thana will be covered by only built-up class by 2041.

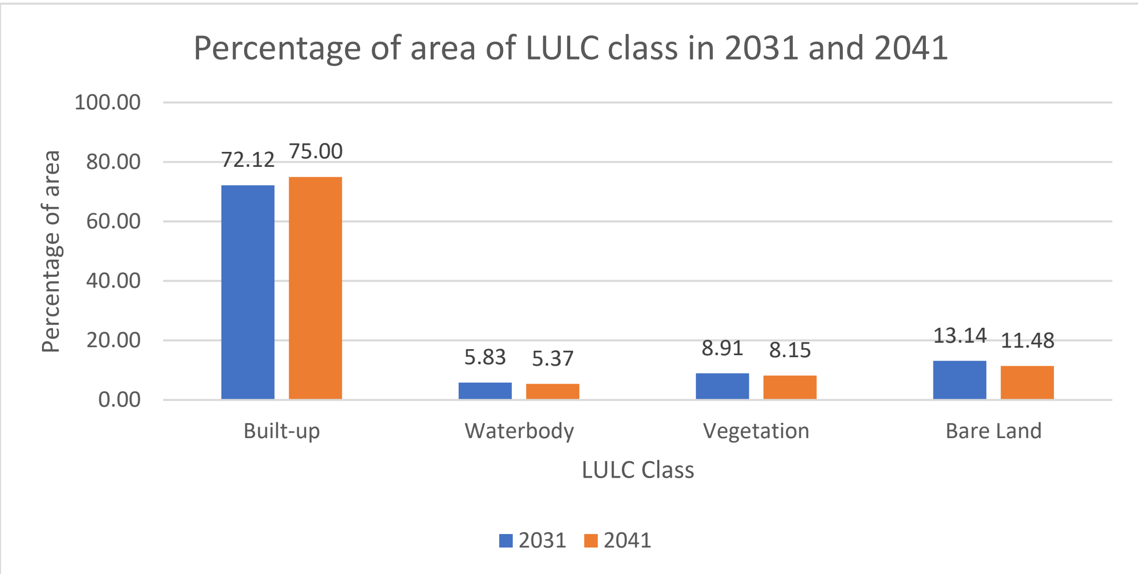


Figure 24: Trend of LULC (projected) changes in area percentage of 2031, 2041

Transition probability matrix as given in Table 18 shows there is high probability of other LULC classes to be converted to built-up and bare land. Waterbody and vegetation have a probability of 24% and 28% to be converted to built-up respectively, while the probability is 48% and 46% for the same. The higher transition percentage to bare land raises an interesting fact even after having only 11.48% of total land area in 2041. The table shows all the other types of LULC classes has the highest percentage of transition probability to bare land. The fact implies that bare land acts as an intermediate land class in the process of LULC transition from one to another classes.

	Built-up	Waterbody	Vegetation	Bare land
Built-up	0.4713	0.0543	0.1313	**0.3431**
Waterbody	**0.2487**	0.0963	0.1659	**0.4891**
Vegetation	**0.2876**	0.0813	0.1644	**0.4667**
Bare land	0.2786	0.0793	0.1657	**0.4765**

Table 18: LULC Transition probability matrix of 2041

This LULC growth presents significant increase of heating factors (built-up/bare land) and a trend of decrease of cooling factor (waterbody/vegetation) in across different areas of the city. However, the spatial progress of heating factors will vary depending on percentage of area covered by identified types of LULC transition phases termed as "1st, 2nd & 3rd Urban Order" in respective thana. Figure 25 illustrates the percentage of area coverage by heating factors because of sequential transition of three different urban orders from the year of 2021 to 2041. As discussed earlier that such transition causes the existence of surface urban heat island effect, therefore it is highly susceptible that those areas are potential to rapid increase of surface heat. Similarly, the lower percentage of area coverage account for a comparatively slow growth of heat intensity. Figure 25 shows Adabor, Mirpur, Pallabi, Tejgaon and Tejgaon Industrial zones will experience an increase of heat at early stage, while Shah Ali, Biman Bandar and Cantonment Thana will face a comparatively slow growth of surface heat.

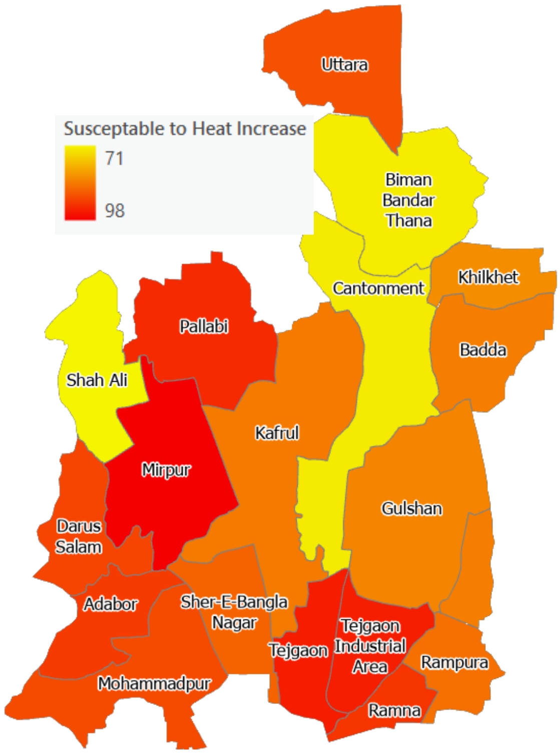


Figure 25: Percentage of projected area coverage by heating factors in respective Thana during 2041

CHAPTER 6: MITITGATION STRATEGY FOR SURFACE HEAT RISK REDUCTION

6.1. Introduction

This chapter provides feedback to reduce the surface heat risk based on LULC transition pattern and impact of socio-economic and physical factors. It describes the unit of measurement as required for heat mitigation as well as suggests the indicators and components of decision making. The points made in this chapter follows the outcome of analysis chapter and calls for a strategic approach using integrated information of urban transitions.

6.2. Means of Measurement

Strategic formulation requires a data driven approach to disseminate respective authority about the logical framework of policy statements. This study generates the quantitative information about status of LULC transition factors associated with Heat Risk. Therefore, such approach removes bias and give a solid foundation for assessing possible impact of relevant factors.

6.2.1. Probability of transition from cooling to heating factors

The analysis proves water and vegetation has negative impact in heat increasing (Table 12) and there is probability that cooling factors will be replaced by propagation of heating factors (built-up/Bare land) over the time across Dhaka North City (Table 18). Moreover, the existing proportion of water and vegetation is minimal (Table 11). So, there is an urgent need to conserve the sources of cooling factors such as green and blue infrastructures. So that it retains in its current state and helps to prevail its contribution to lessen surface heat.

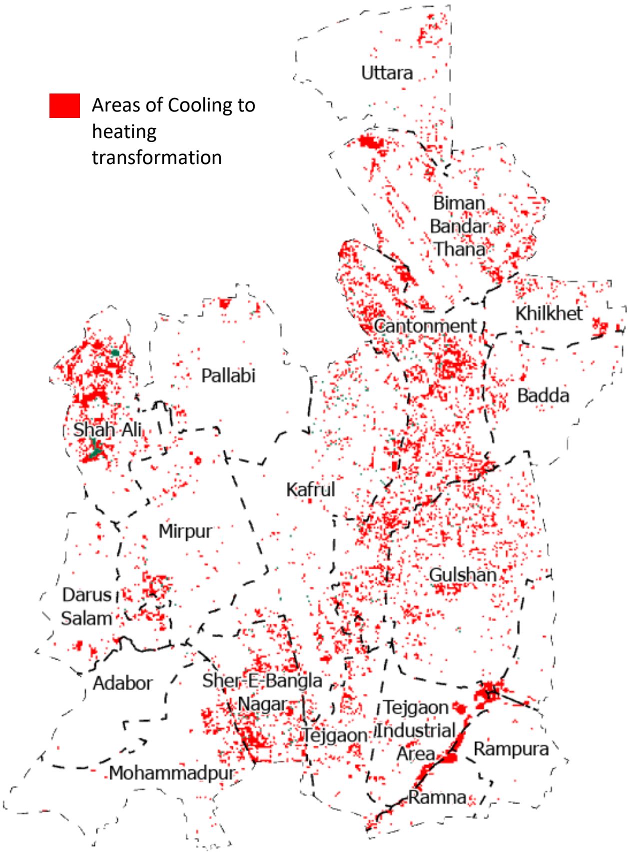


Figure 26: Location of spatial transformation of cooling factor by heating factor

To this end, the authority should undertake the steps to address probable zones of diminishing cooling factors. The study finds two phases of landcover transition where it indicates at which locations vegetation or water body will disappear. Figure 26 presents spatial location of such areas where replacement of waterbody and vegetation will occur by growth of built-up or bare land. Some areas will face an early loss (by 2031) and some areas in later (by 2041). Regardless of the period of loss, the areas of such land transformation should be tackled immediately and imposed restriction on the growth of built-up in cost of vegetation and water body.

Figure 27 shows the Thana wise statistics of the density of area to be transformed from cooling to heating factors in consecutive future decades of 2031 and 2041. It illustrates a major transformation will happen by 2031, while comparatively very less portion of transformation will occur during 2041.

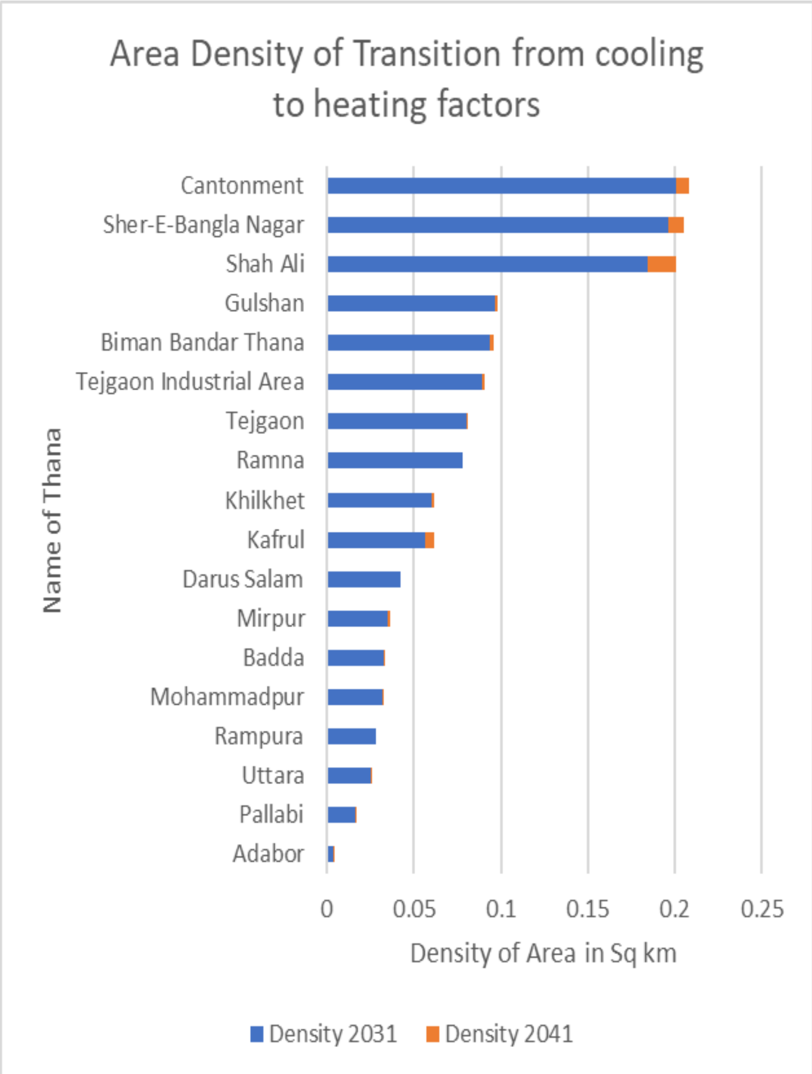


Figure 27: Area density of loss of cooling factor

6.2.2. **Socio-economic and physical profile of Heat Contribution**

As mentioned earlier in analysis chapter, a skewness towards socio-economic index in an area along with significant gap between socio-economic and physical index causes the area to be highly increased in surface temperature over the period. So, an area wise comparative profile between socio-economic and physical index helps in making decision regarding which areas require what kind of approach in a broader context of mitigation. Figure 28 states dynamic relationship between two factors across the Thana areas of the city. Some are attributed to higher social index while some are lower. The same pattern is visible for physical as well. However, a few are equally divided by both factors. This measure helps in strategizing for undertaking the right approach fitting best for a particular area. Thus, authority can decide whether they should focus on physical or social context for mitigation strategy. If an area has higher socio-economic index, then authority should focus on social aspect for heat reduction. Conversely, for higher physical index, risk reduction approach should be based on physical aspect.

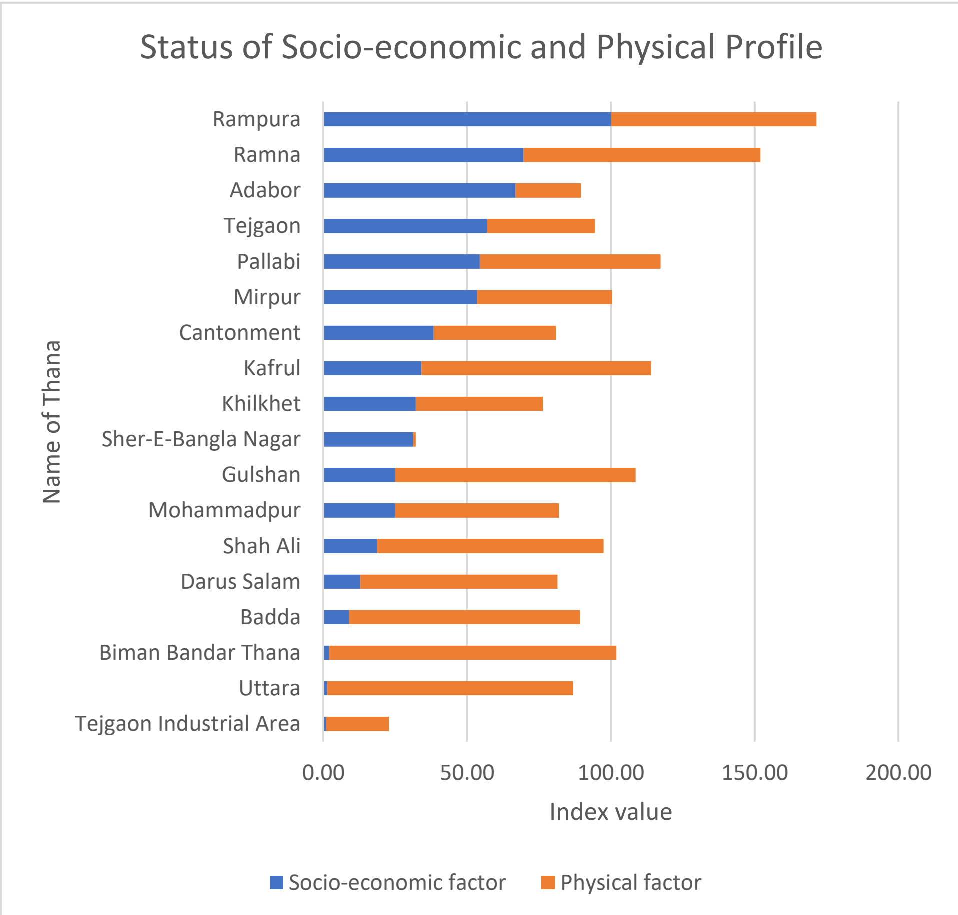


Figure 28: Thana wise intensity of socio-economic and Physical factors

After finalization of strategic focus, it is necessary to identify dominant variable of mitigation. In this way it will be possible to decide which feature of respective Thana should be considered to minimize the risk of SUHI effect. Then, based on the type of effect (positive/negative) of that variable on heat intensity, further measure will be carried out at detailed level plan (Figure 29).

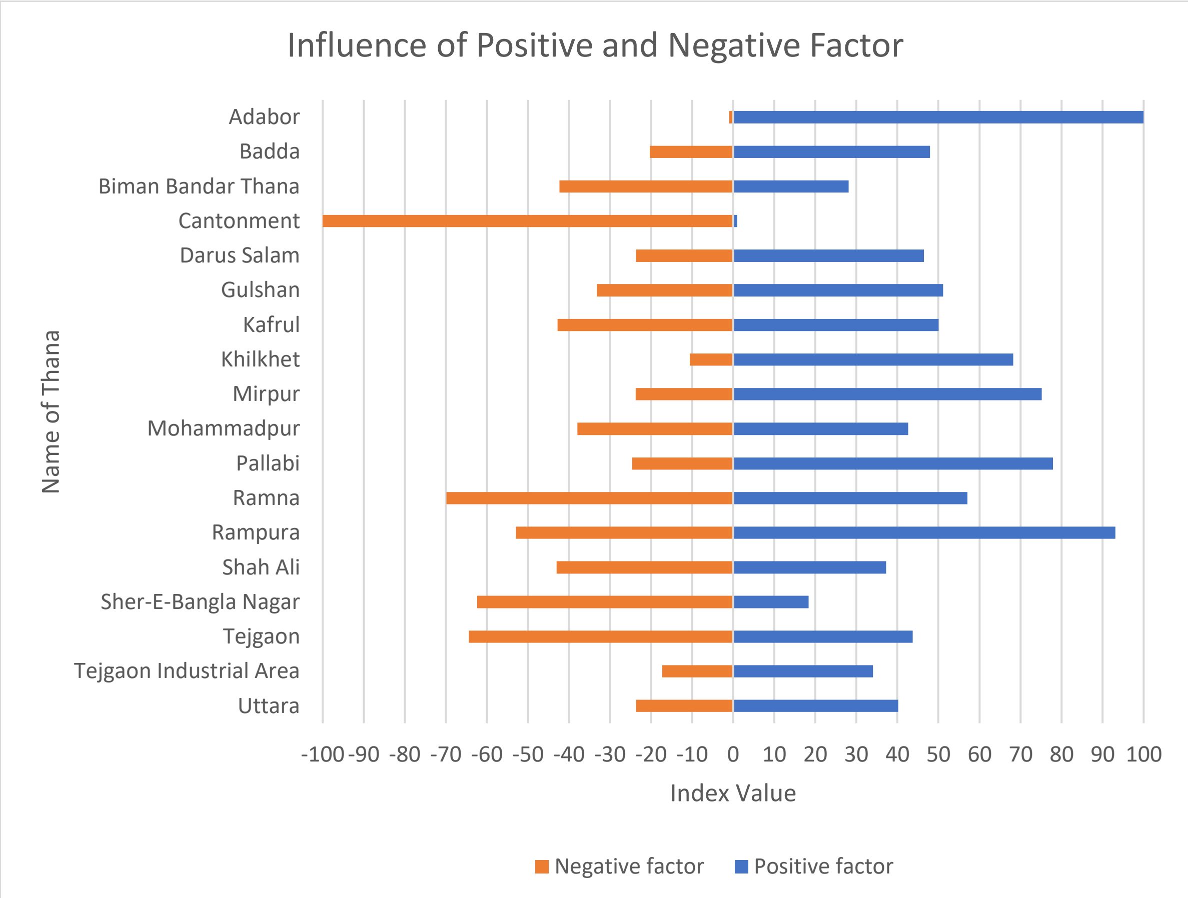


Figure 29: Thana wise intensity of Positive and Negative factors

Following the above strategies, it will be possible to prioritize the zone of influence and will help in taking necessary measures to those areas at first which is highly susceptible to heat risk.

6.3. **Policy Guideline for Surface Urban Heat Risk Reduction**

This chapter finally provides a Thana wise policy guideline for Dhaka North City Corporation following the outcome of above discussion based on the output of analysis using LULC transition pattern and relative impact of both factors. The details of policy guideline for surface urban heat risk reduction have been discussed as follows.

The strategic approach considers four tiers of scenario for each Thana area to finalize guidelines for mitigation of surface urban heat risk at local (Thana) scale. In the study area, 52 numbers of authority are working for social and infrastructural development. Regardless of area of work, the below scenarios can be considered by any organization who are working on either of the variables under both type of factors. The scenarios have been discussed in Table 19.

SL	Scenario	Indicator
1	Temporal Impact of LULC Transition Pattern	All the 18 areas have been raked according to area density of probable transition from cooling to heating factor. The value of 1 represents an earliest impact of transformation to heating factors, whereas with gradual increase of Ranking value shows a later impact transformation scenario. Areas with lower order of rank are comparatively highly susceptible to heat increase.
2	Area of Strategic Focus	The quadrantal position and index value of each area defines the approach. This scenario indicates whether the approach to be undertaken should focus on existing socio-economic or physical attributes of the area as part of risk reduction initiative.
3	Dominance level of Variables	The variable with highest portion among all other is defined as the most Dominant variable. Because of its existence on top position among all in respective Thana, Risk reduction strategy can be fostered by taking necessary action depending on its type of influence. An order of priority of dominant variables can be listed depending on the scope of work. As this study focuses on heat risk reduction, therefore it is necessary to find the existing intensity of such features which contributes to reduce surface heat.
4	Effect of variable	Once the dominant variable/variables are selected, the next step is to evaluate the effect. Positive effect suggests for a reduction of intensity of related variables, while negative effect suggests for possible increase of its intensity. Therefore, selecting features of negative effect as a tool for mitigation on heat increase would be effective and efficient.

Table 19: Scenario and Indicators of Heat Mitigation Plan

The scenarios are the deciding factors for respective authority and decision makers controlling development of the jurisdiction. Based on the deciding factors and means of measurement, the components of Heat Risk Reduction Strategies have been described below. The impact of mitigation strategies depends on the efficiency of selected measures. The below components should be considered to get maximum output from mitigation strategy.

Component 1: Priority areas of action

According to figure 25, there are areas with comparatively higher potential to heat increase because of the effect of higher coverage of three orders of urban transition phases. Therefore, the output can be utilised as a strategy to define which areas has possibility to increase surface heat at earlier stage. Strategically, areas with a possibility of heat increase at an early stage should be positioned on the top list of mitigative action. So that, it becomes possible for decision makers to categorise areas by short-term and long-term measures. Thus, this enables authority to take immediate action against heat risk on those areas which will face a comparatively rapid and early growth of heating factors such as built-up and bare land. Conversely, areas with possibility of heat increase at slow rate as well as at later stage of time, can be suitable for a long term mitigative measures. For dissemination purpose, the areas can be presented quarterly (on ascending order) in a one-day clock scale (00 to 24 hours) according to the information of area percentage (Figure 25) in terms of early and later impact respectively. The temporal unit of mitigation response has been represented in table 20. The areas existing in 1st quarter of response requires an immediate action of mitigation, while areas of 8th quarter can be later in priority list of mitigation action.

Time of Day/Order of Response	Areas of Priority	Time of Day	Areas of Priority
1st Quarter 01:00 – 03:00	➢ Mirpur ➢ Tejgaon ➢ Tejgaon Industrial Area	5th Quarter 13:00 – 15:00	➢ Badda ➢ Gulshan ➢ Khilkhet
2nd Quarter 04:00 – 06:00	➢ Pallabi ➢ Ramna ➢ Adabor	6th Quarter 16:00 – 18:00	No areas
3rd Quarter 07:00 – 09:00	➢ Darus Salam ➢ Mohammadpur ➢ Uttara	7th Quarter 19:00 – 21:00	➢ Cantonment
4th Quarter 10:00 – 12:00	➢ Sher-E-Bangla Nagar ➢ Rampura ➢ Kafrul	8th Quarter 22:00 – 24:00	➢ Biman Bandar Thana ➢ Shah Ali

Table 20: Unit of temporal response order for heat mitigation action

Component 2: Strategic Approach

Depending on the contribution of factors on surface heat increase, mitigative approach can be adopted. Identification of types of contribution by factor is important as it provides information about the skewness of the area towards a particular factor. A socio-economic skewed area with higher level of discrepancy from physical factor has higher potential to heat risk. Whereas skewness towards physical factors depicts a low profile for heat intensity. This interaction further describes that socio-economic attribute triggers the urban functionality of an area and hence it has an indirect effect on heat increasing by reducing the portion of cooling factors from that area. Thus, with a higher land consumption rate by urban class (built-up), the area continues to loss the portion of cooling factors, as discussed in section 6.2.1. On the other hand, a low-socio-economic and high physical profile does not support the principle of sustainable development as it will create more discrepancy on the other Thana area of the city. Therefore, the socio-physical profile is necessary for concerned authority to understand about the ratio between factors. The ratio can be helpful for decision makers to ensure a balance between both factors by evaluating their quadrantal position. Figure 30 illustrates relative contribution of factors for individual Thana. The areas located in the High socio-economic and low physical zone are highly susceptible for heat increase and the mitigative measure should focus reducing the contribution of population agglomeration and urban functionality of that area. The areas within low socio-economic quadrant can be preferred for further consumption of land by population. Therefore, development strategies of individual area in the city should follow such approach so that all the areas reach or remain close to the optimum point of quadrant.

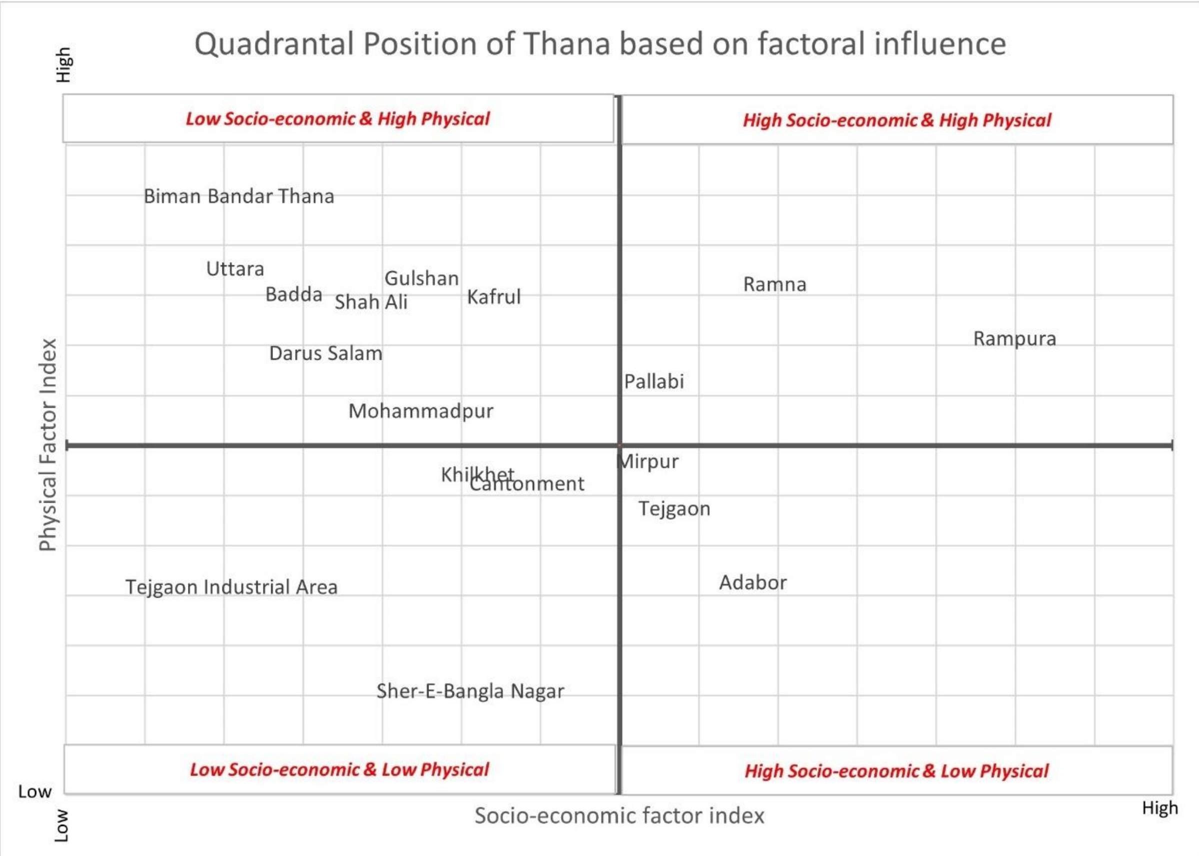


Figure 30: Category of Thana by relative influence of socio-economic & physical factors

Component 3: Capacity of Resources

Heat Mitigation requires a systematic management and utilization of existing resources within the area. This study has discussed earlier about the influence of relevant socio-economic and physical features on heat intensity. The feature which prevails at a higher percentage in a particular Thana have naturally stronger influence on heat change. However, on the other hand the analysis finds that physical features with negative effect on heat change contribute on surface heat reduction. Therefore, to optimize the mitigation effect, area coverage of negatively correlated physical features (Table 16) such as waterbody density, SVF and vegetation density should be either conserved or maximized depending on study area profile. This study further supports decision makers by sharing the information about total percentage of area coverage by negative physical factors within area of respective Thana across Dhaka North City Corporation.

Thus, a strategic utilisation of such resources as a primary tool of mitigation process will be more effective, rather than considering other random existing features as a mitigation tool contained within the study area. In this regard, Figure 31 presents mitigation readiness map of Dhaka North City Corporation area indicating a higher capacity of mitigation resources with higher percentage. the low percentage area indicates low capacity of existing resources to mitigate surface heat intensity. Therefore, the information will be supporting for decision makers to understand at what level further proposed development will hamper existing tools of mitigation. Also, it suggests the type of mitigation measures in development plan proposals so that the three negative physical features remain at least in its current ratio or improve further. This ratio will further provide guidelines about the required threshold amount of water body or vegetation (in either terms such as open space plantation, rooftop greening etc.) or openness to sky view for a particular zone in the city. As per readiness map Biman Bandar Thana possesses 60% (highest) capacity to utilise its resources for heat mitigation, whereas the capacity is lowest in Mirpur with 6.46%.

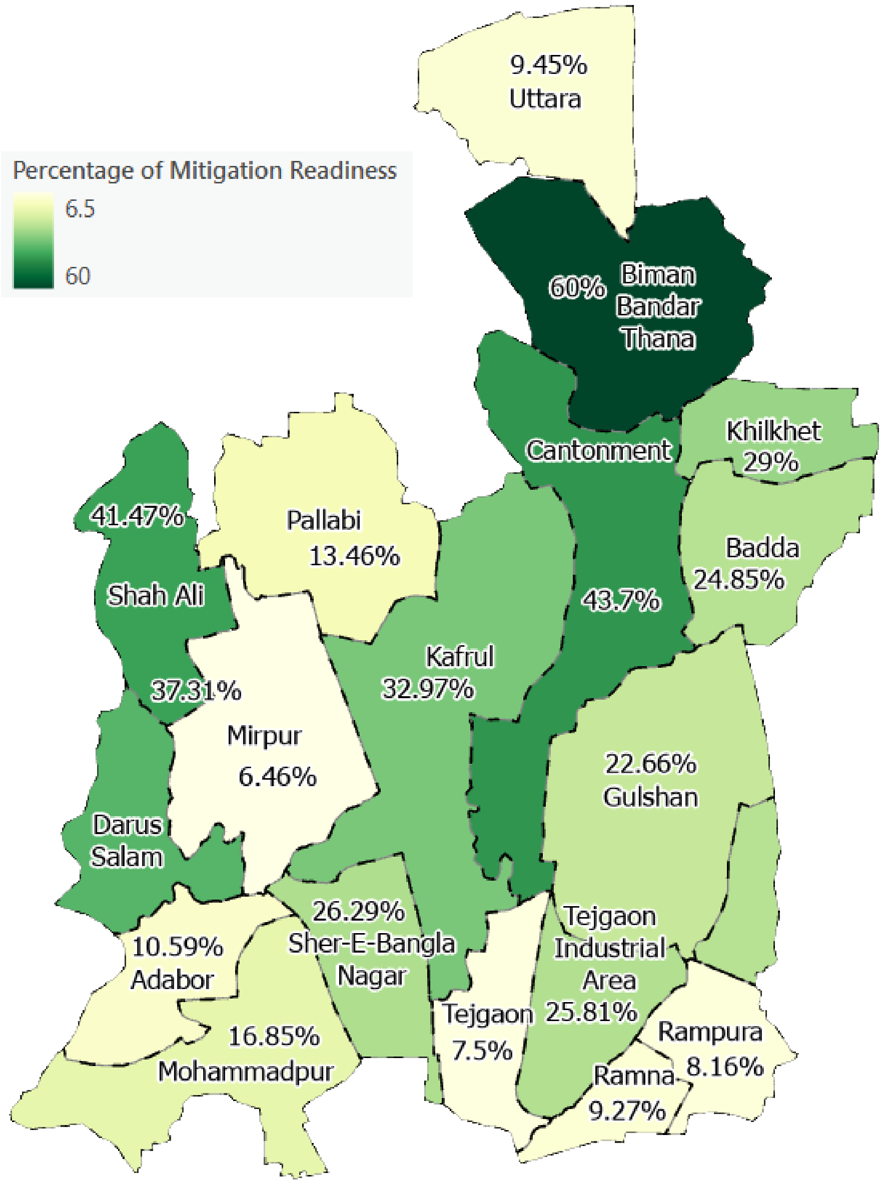


Figure 31: Mitigation Readiness Map of Dhaka North City Corporation

All the above discussed policy measures are supportive in mitigation of increasing pattern of heat risk by using relevant factors and component of LULC transition pattern including influence of social and physical aspect.

6.4. Discussion and Remarks

The study prepares a measurable mitigation profile for each administrative unit of the city which further helps local government to distribute and allocate climate finance as per area of priority. The LULC growth of previous years shows regular pattern of built-up growth and decline of waterbody, vegetation and bare land. Although this is the only study conducted specifically for Dhaka North City Corporation, while other studies analyse LULC pattern of greater areas of Dhaka. However, the pattern of LULC changes in all classes are found similar. Faisal et. al., (2021) demonstrate a similar growth pattern and accounts for a net change of + 20.52%, -3.6%, -5.72% and 11.19% for built-up waterbody, vegetation and bare land for the Dhaka Metropolitan Area (DMA) during 2000 to 2020. The DMA area land class change shows a significant less decline for waterbody, whereas for comparatively much higher decline appears for Dhaka North City Corporation.

In finding of importance of type of associated factors such as socio-economic and physical, the study brings the idea of factor influence in in collective way rather than concentrating individual correlation of variables of either factor with heat increase. Previous studies discuss mainly the relationship of satellite derived indices as a proxy of urban features such as Normalised Differential Water Index, Normalised Differential Building Index, Night-time light etc. to quantify density about water, building, population respectively (Xiong et al., 2012; Kant et al., 2009; Christopher et. al., 2001). This study calculates GIS and statistical data for extracting density of information, which is considered more precise and accurate, not relying on proxy measurement. The only indices use in this study is NDVI, because of unavailability of vegetation GIS data for the area. NDVI shows a weak negative correlation with SUHI intensity. Moreover, comparing the index of both factor with LST represents a collective effect of variables on heat increase pattern, which is the actual scenario of UHI effect in a city environment. Because UHI is the result of accumulated actions by all the related variables un both factors. Therefore, this study has become able to bring a collective scenario analysis of heat intensity by urban activities.

The predicted LULC maps defines some areas to be experiencing rapid heat propagation. The results show study area will face maximum coverage of susceptible LULC transition by 2031 at rapid rate, while a few will occur during next decades. Faisal et. al., (2021) predicts the spread of Urban Thermal Field Variance Index (UTFVI) in Dhaka City and finds the rise of stronger UTFVI by 16.43% in summer 2030.

According to findings in this research, transformation of bare land to built-up has occured in the peripheral area of the city such as Uttara, Adabor and Khilkhet. Therefore, this brings the question if urban sprawl has has a positive and indirect effect in heat increase. As it is also found all the vegetation and water class has high probability to be converted to bare land. Therefore, the scenario implies the possibility of urban sprawl in cost of cooling factors. According to prediction map, due to lack of remaining open land in the city, the land transformation of heating factor will occur in those areas currently occupied by cooling factors. Analysing effect of variables, The Thana area which has higher level of shading area percentage are prone to high heat intensity. Although, shading is considered as cooling effect for UHI at micro scale, but this larger scale analysis shows that an increase of shading might cause hot environment because of indirect effect of tall buildings effect. similar findings appeared for affordable, and electricity connected households in the city. Normally, areas with more affordable housing and electricity connection supposed to cause higher heat in the area because of it high level of indirect socio-economic consumption characteristics. But the findings show opposite scenario and according to correlation result, these variables are found as negative factor for heat increase. this scenario can be described as the lower affordability causes less access to better living environment in terms of proximity to cooling factors. The area mostly occupied by lower percentage of affordable housing are more potential to heat increase because of less amount of existence of vegetation and greeneries in that area. Moreover, it is necessary to find if LST increases with the type of building materials commonly used by low-income houses such as tin-shed house. This study finds a high surface temperature on those areas particularly occupied by tin-shed houses such as Karail slum of Gulshan. Therefore, it is important to consider aspect of factors in reducing the risk of surface temperature.

While building density is found as a positive feature of heat increase, Sky View Factor (SVF) shows a stronger physical variables negatively related with heat increase. Therefore, to supplement growth of the primate capital city of Dhaka, careful consideration needs to be taken in terms of heat mitigation. Apparently, the simple decision of stopping building construction in most heat susceptible zone might sound a feasible decision. But a technical formation of urban design such as high considering high SVF during construction might be a suitable solution of heat mitigation in such a fast growing and economically important city like Dhaka.

CHAPTER 7: CONCLUSION AND RECOMMENDATION

7.1. Conclusion

A systematic mitigation strategy to reduce the risk of surface heat island is an urgent need for local government authorities to tackle the adverse impact of climate change and at the same time continue to support urban growth. The goal of this study is to provide necessary information as required for undertaking specific mitigation actions for a particular Thana of Dhaka North city Corporation. Using Spectral and thermal Satellite sensors of Landsat satellite, it has become possible to extract accepted level of accurate Land Surface Temperature (LST) and Landuse Landcover (LULC) map for the year of 2001, 2011 and 2021 respectively. While the absolute LST value of each year might represent bias because of seasonality, Normalized LST (NLST) map provides the relativity of surface temperature for specific year and is used as a well-accepted parameter to compare increased unit of heat in different years. In this study, NLST map is the source of base information which indicates areas of highest surface heat difference over the decades. The highest threshold area of heat increased is the indicator to identify pattern of LULC transition and factor contribution triggering the increasing trend of Surface Urban Heat Island (SUHI). The intersection result shows variety of LULC transition pattern overlying the area of hi-moderate surface heat increase zone, which is later considered as a susceptible type of land transform responsible for creating high heat surface in the study area. The output of this transition is further classified into three order of transition phases based on development decades of built-up class. This order indicated the area possesses an earlier development history of built-up class have strong probability of surface heat increase. the composition of LULC transition also describes in the hi-moderate surface increase heat zone built-up areas has been developed replacing existing cooling factors such as vegetation and waterbody.

On the other hand, the relative factor analysis output demonstrates if a Thana is skewed towards social index, the area can be considered to become a heat centre zone of the city. Higher Socio-economic intensity means the area has higher level of urban activity regularly performed by population from inner and outer side of the boundary. In this context, the study outlines that related socio-economic variables are more influential for increasing surface temperature than that of physical variables based on the human behaviour on that land.

However, in reducing heat intensity of surface physical factor play stronger role that socio-economic. This refers to an increase of negative physical factor will be comparatively higher influential in reducing SUHI effect rather than reducing the concentration of socio-economic variables. Therefore, in mitigating surface heat island effect, the focus should be given to physical negative factor to get a short-term benefit. On the other hand, socio-economic variables will be effective for long term mitigation plan as it has a slower but stronger impact over surface heat intensity.

Mitigation actions require existing resource capacity of both man-made and natural features, and the efficiency of action can be fostered by optimal investment. As a third world nation, Bangladesh lacks the financial capacity to invest on climate adaptation and mitigation. The mitigation strategy suggested in this study direct authority a cost-effective guideline by sharing information about probable heat susceptible zones, area of strategic focus and capacity of existing mitigation tools. The guideline will be supportive for concerned authority who are working on social and physical development of the area to continue development work considering climate sensitivity of the area.

7.2. Limitation

1. This study focuses on the local administrative boundary within a city. The statistical data used in this research is from the census of 2011, there are no other statistical data source at this detail level recently published by any government and non-government organization. Therefore, this study assumes that variables of socio-economic factor will follow a linear growth over decades.
2. Due to unacceptable cloud coverage the study could not consider satellite images collected during summertime of respective years to get the highest scenario of surface temperature. However, the effect of seasonality is minimized by normalization.
3. Due to formation of Dhaka North City Corporation in 2011, there is no updated census available comprising of specific study area information. Most of the data found for Dhaka City including newly formed North and South City Corporation. Therefore, this study lacks some detail information about study area.

7.3. Further Scope of Research

The study provides local scale mitigation plan with broad category variables. Based on the outputs of mitigation strategy, micro scale mitigative action can be interesting area of study followed by principles of city scale mitigation proposals as suggested in this study. There is scope of conducting further detailed research on evaluating dynamic relationship between variables as a source of surface heat intensity.

CHAPTER 8: **REFERENCE**

1. Ahmed, Sohel & Nahiduzzaman, Kh Md & Bramley, Glen. (2014). From a Town to a Megacity: 400 Years of Growth. 10.1007/978-94-007-6735-5_2.
2. Anderson, J. R., Hardy, E. E., Roach, J. T. and Witmer, R. E. (1976). A land use and land cover classification system for use with remote sensor data. USGS Professional Paper 964, U.S. Geological Survey.
3. Bala, R., Prasad, R. & Yadav, V.P., 2021. Quantification of urban heat intensity with land use/land cover changes using Landsat satellite data over urban landscapes. Theor Appl Climatol 145, 1–12. https://doi.org/10.1007/s00704-021-03610-3.
4. Basu A. Das S., 2021. Afforestation, revegetation, and regeneration: a case study on Purulia district, West Bengal (India), Chapter 22, Editor(s): Gouri Sankar Bhunia, Uday Chatterjee, Anil Kashyap, Pravat Kumar Shit, Modern Cartography Series, Academic Press, Volume 10, Pages 497-524, ISSN 1363-0814, ISBN 9780128238950, https://doi.org/10.1016/B978-0-12-823895-0.00014-2.
5. Cai, Y.; Zhang, H.; Zheng, P.; Pan,W., 2016. Quantifying the Impact of Land Use/Land Cover Changes on the Urban Heat Island: A Case Study of the Natural Wetlands Distribution Area of Fuzhou City, China. Wetlands, 36, 285–298.
6. Carlson, T.N., & Ripley, D.A. (1997). On the relation between NDVI, fractional vegetation cover, and leaf area index. Remote Sensing of Environment, 62, 241–252.
7. Chapman S. Watson J, Salazar P. A. Thatcher, M. McAlpine, C. 2017, The impact of urbanization and climate change on urban temperatures: a systematic review. Landscape Ecology. 32(10):1921-1935. https://doi.org/10.1007/s10980-017-0561-4.
8. Chen, Z. Gong C. Wu J. Yu S., 2012. The Influence of Socioeconomic and Topographic Factors on Nocturnal Urban Heat Islands: A Case Study in Shenzhen, China. Int. J. Remote Sens. 33, 3834–3849.
9. Cui, L.; Shi, J., 2012. Urbanization and Its Environmental Effects in Shanghai, China. Urban Climate. 2, 1–15.
10. Dare P., 2005. Shadow Analysis in High-Resolution Satellite Imagery of Urban Areas. Photogrammetric Engineering & Remote Sensing. 71. 169-177. 10.14358/PERS.71.2.169.
11. Degirmenci, K.; Desouza, K.C.; Fieuw, W.; Watson, R.T.; Yigitcanlar, T., 2021. Understanding Policy and Technology Responses in Mitigating Urban Heat Islands: A Literature Review and Directions for Future Research. Sustain. Cities Soc. 70, 102873.

12. Deilami, K.; Kamruzzaman, M.; Hayes, J.F., 2016. Correlation or Causality between Land Cover Patterns and the Urban Heat Island Effect? Evidence from Brisbane, Australia. Remote Sens. 8, 716.
13. Derdouri, A.;Wang, R.; Murayama, Y.; Osaragi, T., 2021. Understanding the Links between LULC Changes and SUHI in Cities: Insights from Two-Decadal Studies (2001–2020). Remote Sens. 13, 3654. https://doi.org/10.3390/rs13183654
14. Dey N. N. Abdullah Al Rakib, Abdulla - Al Kafy, Vinay Raikwar. 2021. Geospatial modelling of changes in land use/land cover dynamics using Multi-layer Perceptron Markov chain model in Rajshahi City, Bangladesh, Environmental Challenges, Volume 4, 100148, ISSN 2667-0100, https://doi.org/10.1016/j.envc.2021.100148.
15. Dihkan, M., Karsli, F., Guneroglu, N. et al., 2018. Evaluation of urban heat island effect in Turkey. Arab J Geosci 11, 186. https://doi.org/10.1007/s12517-018-3533-3
16. Dutta I. Das A., 2020. Exploring the Spatio-Temporal Pattern of Regional Heat Island (RHI) in an Urban Agglomeration of Secondary Cities in Eastern India. Urban Clim, 34, 100679.
17. Estrada F. Botzen W. Tol R. A., 2017. global economic assessment of city policies to reduce climate change impacts. Nature Clim Change 7, 403–406. https://doi.org/10.1038/nclimate3301
18. Faisal A. Kafy A. Rakib A. A. Kaniz Shaleha Akter, Dewan Md. Amir Jahir, Md. Soumik Sikdar, Tahera Jahan Ashrafi, Saumik Mallik, Md. Mijanur Rahman., 2021. Assessing and predicting land use/land cover, land surface temperature and urban thermal field variance index using Landsat imagery for Dhaka Metropolitan area, Environmental Challenges, Volume 4, 100192, ISSN 2667-0100, https://doi.org/10.1016/j.envc.2021.100192.
19. Fan C. Myint, S.W.; Kaplan, S.; Middel, A.; Zheng, B.; Rahman, A.; Huang, H.-P.; Brazel, A., 2017. Blumberg, D.G. Understanding the Impact of Urbanization on Surface Urban Heat Islands-A Longitudinal Analysis of the Oasis Effect in Subtropical Desert Cities. Remote Sens. 9, 672.
20. Feng H. Zhao X. Chen F. Wu L., 2014. Using land use change trajectories to quantify the effects of urbanization on urban heat island, Advances in Space Research, Volume 53, Issue 3, 2014, Pages 463-473, ISSN 0273-1177, https://doi.org/10.1016/j.asr.2013.11.028.
21. Gawuc L. Lobocki L. Struzewska J., 2022. Application of the profile method for the estimation of urban sensible heat flux using roadside weather monitoring data and satellite imagery, Urban Climate, Volume 42, 2022, 101098, ISSN 2212-0955, https://doi.org/10.1016/j.uclim.2022.101098.

22. Ghosh, S.; Das, A., 2018 Modelling Urban Cooling Island Impact of Green Space and Water Bodies on Surface Urban Heat Island in a Continuously Developing Urban Area. Model. Earth Syst. Environ. 4, 501–515.
23. Giridharan R., Emmanuel R., 2018. The impact of urban compactness, comfort strategies and energy consumption on tropical urban heat island intensity: a review. Sustainable Cities and Society, 40, 677-687.
24. Grimmond, S., 2007. Urbanization and Global Environmental Change: Local Effects of Urban Warming, 173, 83–88.
25. Gunawardena K. R. Wells M. J. Kershaw T. 2017. Utilising green and bluespace to mitigate urban heat island intensity. The Science of the Total Environment, 584-585, 1040–1055.
26. Han J. Kamber M. Pei J., 2012. Data Preprocessing, In The Morgan Kaufmann Series in Data Management Systems, Data Mining (Third Edition), Chapter 3, 2012, Pages 83-124, ISBN 9780123814791, https://doi.org/10.1016/B978-0-12-381479-1.00003-4.
27. Hanna E.G. Kjellström, T. Bennett C. Dear K., 2011. Climate change and rising heat: population health implications for working people in Australia. Asia-Pacific Journal of Public Health 23: 2.
28. Huang F. Zhan W. Voogt J. Hu L. Wang Z. Quan J. Ju W. Guo Z., 2016. Temporal upscaling of surface urban heat island by incorporating an annual temperature cycle model: A tale of two cities, Remote Sensing of Environment, Volume 186. Pages 1-12, ISSN 0034-4257, https://doi.org/10.1016/j.rse.2016.08.009.
29. Huang X. & Wang Y., 2019. Investigating the effects of 3D urban morphology on the surface urban heat island effect in urban functional zones by using high-resolution remote sensing data: A case study of Wuhan, Central China, ISPRS Journal of Photogrammetry and Remote Sensing, Volume 152, Pages 119-131, ISSN 0924-2716, https://doi.org/10.1016/j.isprsjprs.2019.04.010.
30. Huang X. Wang Y. 2019. Investigating the effects of 3D urban morphology on the surface urban heat island effect in urban functional zones by using high-resolution remote sensing data: A case study of Wuhan, Central China, ISPRS Journal of Photogrammetry and Remote Sensing, Volume 152, Pages 119-131, ISSN 0924-2716, https://doi.org/10.1016/j.isprsjprs.2019.04.010.
31. Imhoff M. L. Zhang P. Wolfe R.E. Bounoua L., 2010. Remote sensing of the urban heat island effect across biomes in the continental USA, Remote Sensing of Environment,

Volume 114, Issue 3, Pages 504-513, ISSN 0034-4257, https://doi.org/10.1016/j.rse.2009.10.008.

32. IPCC, 2014. Climate change 2014: synthesis report. In: Team, C.W., Pachauri, R.K., Meyer, L.A. (Eds.), Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Geneva, Switzerland.
33. Islam, M. S., Rahman, M. R., Shahabuddin, A., & Ahmed, R. (2011). Changes in wetlands in Dhaka City: Trends and physico-environmental consequences. Journal of Life and Earth Science, 5, 37–42. https://doi.org/10.3329/jles.v5i0.7348.
34. Jusuf S. K. Wong N. H. Hagen E. Anggoro R. Hong Y., 2007. The influence of land use on the urban heat island in Singapore. Habitat International, 31(2), 232–242.
35. KABIR, A. & PAROLIN, B., 2012. n.d. PLANNING AND DEVELOPMENT OF DHAKA – A STORY OF 400 YEARS. s.l., s.n.
36. Kafy A. A. Dey N. N. Rakib A. A. Rahaman Z. A. Nasher N. M. Bhatt. A., 2021. Modelling the relationship between land use/land cover and rfac temperature in Dhaka, Bangladesh using CA-ANN algorithm, Environmental Challenges, Volume 4, 100190, ISSN 2667-0100, https://doi.org/10.1016/j.envc.2021.100190.
37. Kafy A.A. Faisal A. A. Rahman S. M. Islam M. Rakib A. Islam A. M. Khan H. H. M. Sikdar S. M. Sarker H. S. M. Mawa J. Sattar S. G., 2021. Prediction of seasonal urban thermal field variance index using machine learning algorithms in Cumilla, Bangladesh, Sustainable Cities and Society, Volume 64, 102542, ISSN 2210-6707, https://doi.org/10.1016/j.scs.2020.102542.
38. Kamal, S., 1993. Social Formation in Dhaka City. Dhaka, Bangladesh: University Press LImited.
39. Kant, Y.; Bharath, B.D.; Mallick, J.; Atzberger, C.; Kerle, N., 2009. Satellite-Based Analysis of the Role of Land Use/Land Cover and Vegetation Density on Surface Temperature Regime of Delhi, India. J. Indian Soc. Remote Sens. 37, 201–214.
40. Ke X. Ma E & Yongwei Y., 2014. Scenario Simulation of the Influence of Land Use Change on the Regional Temperature in a Rapidly Urbanizing Region: A Case Study in Southern-Jiangsu, China. Advances in Meteorology. 2014. 1-12. 10.1155/2014/159724.
41. Kikon, N.; Singh, P.; Singh, S.K.; Vyas, A., 2016. Assessment of Urban Heat Islands (UHI) of Noida City, India Using Multi-Temporal Satellite Data. Sustain. Cities Soc. 22, 19–28.
42. Kleerekoper, L.; van Esch, M.; Salcedo, T.B., 2012. How to Make a City Climate-Proof, Addressing the Urban Heat Island Effect. Resour. Conserv. Recycl. 64, 30–38.

43. Larsson D., 2000. Developing the structure of a Fire Risk Index method for timber-frame multi-storey apartment building, Lund, Sweden: Lund University, ISSN 1402-3504, http://lup.lub.lu.se/student-papers/record/1687186
44. Lee K. & Kim, Yoonji & Sung, Hyun & Kim, Seung & Jeon, Seongwoo. (2021). Changes in Urban Heat Island Effect with the Development of Newtowns. 10.21203/rs.3.rs-382802/v1.
45. Li D. Liao W. Rigden A. J. Liu X. Wang D. Malyshev S. Shevliakova E., 2019. Urban heat island: Aerodynamics or imperviousness?. Science Advances, 5, eaau4299.
46. Li Y. Zhang H. Kainz W., 2012. Monitoring patterns of urban heat islands of the fast-growing Shanghai metropolis, China: Using time-series of Landsat TM/ETM+ data, International Journal of Applied Earth Observation and Geoinformation, Volume 19, Pages 127-138, ISSN 1569-8432, https://doi.org/10.1016/j.jag.2012.05.001.
47. Li Z. Tang B. Wu H., Ren H. Yan H. Wan Z. Trigo I. F. Sobrino J.A., 2013. Satellite-derived land surface temperature: Current status and perspectives, Remote Sensing of Environment, Volume 131, Pages 14-37, ISSN 0034-4257, https://doi.org/10.1016/j.rse.2012.12.008.
48. Li X. Stringer L. C. Chapman S. Dallimer M., 2021. How urbanisation alters the intensity of the urban heat island in a tropical African city. PLOS ONE 16(7): e0254371. https://doi.org/10.1371/journal.pone.0254371
49. Li, X., Zhou, W., Ouyang, Z., 2013. Relationship between land surface temperature and spatial pattern of greenspace: What are the effects of spatial resolution? Landscape Urban Plan. 114, 1–8.
50. Liu, L.; Zhang, Y., 2011. Urban Heat Island Analysis Using the Landsat TM Data and ASTER Data: A Case Study in Hong Kong. Remote Sens. 3, 1535-1552. https://doi.org/10.3390/rs3071535 .
51. Magli S. Lodi C. Lombroso L. Muscio A. Teggi S., 2015. Analysis of the urban heat island effects on building energy consumption. International Journal of Energy and Environmental Engineering, 6(1), 91–99.
52. Mallick J. Rahman A. Singh C. K., 2013. Modelling urban heat islands in heterogeneous land surface and its correlation with impervious surface area by using night-time ASTER satellite data in highly urbanizing city, Delhi-India, Advances in Space Research, Volume 52, Issue 4, Pages 639-655, ISSN 0273-1177, https://doi.org/10.1016/j.asr.2013.04.025.
53. Mallick J. Rahman A. Singh C. K., 2013. Modelling urban heat islands in heterogeneous land surface and its correlation with impervious surface area by using night-time ASTER

satellite data in highly urbanizing city, Delhi-India, Advances in Space Research, Volume 52, Issue 4, Pages 639-655, ISSN 0273-1177, https://doi.org/10.1016/j.asr.2013.04.025 .

54. Mamun, A. A., Mahmood, A., & Rahman, M. (2013). Identification and Monitoring the Change of Land Use Pattern Using Remote Sensing and GIS: A Case Study of Dhaka City. IOSR Journal of Mechanical and Civil Engineering, 20-28.
55. Mani M. Bandyopadhyay S. Chonabayashi S. Markandya A. Mosier T., 2018. South Asia's Hotspots : Impacts of Temperature and Precipitation Changes on Living Standards. South Asia Development Matters;. Washington, DC: World Bank. © World Bank. https://openknowledge.worldbank.org/handle/10986/28723 License: CC BY 3.0 IGO."
56. Manoli G. Fatichi S. Schläpfer M. Yu K. Crowther T. W. Meili N. Burlando P. Katul G.G. Bou-Zeid E. 2019. Magnitude of urban heat islands largely explained by climate and population. Nature, 573, 55-60.
57. Mehmood, R., Butt, M.A., 2019. Appraisal of Urban Heat Island Detection of Peshawar Using Land Surface Temperature and Its Impacts on Environment. J Indian Soc Remote Sens 47, 1091–1096. https://doi.org/10.1007/s12524-018-0924-6.
58. Mohamed E. H., 2017. Retrieving spatial variations of land surface temperatures from satellite data–Cairo region, Egypt, Geocarto International, 32:5, 556-568, DOI: 10.1080/10106049.2016.1161077.
59. Moniruzzaman M. Thakur, P.K. Kumar, P. Ashraful M. A. Garg, V. Rousta I. Olafsson, H. 2021. Decadal Urban Land Use/Land Cover Changes and Its Impact on Surface Runoff Potential for the Dhaka City and Surroundings Using Remote Sensing. Remote Sens., 13, 83. https://doi.org/10.3390/ rs13010083.
60. Mottet A, Sylvie Ladet, Nathalie Coqué, Annick Gibon,, 2006. Agricultural land-use change and its drivers in mountain landscapes: A case study in the Pyrenees, Agriculture, Ecosystems & Environment, Volume 114, Issues 2–4, Pages 296-310, ISSN 0167-8809, https://doi.org/10.1016/j.agee.2005.11.017.
61. Nahrin, K. (2020), "Environmental area conservation through urban planning: case study in Dhaka", Journal of Property, Planning and Environmental Law, Vol. 12 No. 1, pp. 55-71. https://doi.org/10.1108/JPPEL-11-2018-0033
62. Neema, M. , Maniruzzaman, K. and Ohgai, A. (2013) Green Urbanism Incorporating Greenery-Based Conceptual Model towards Attaining a Sustainable Healthy Livable Environment—Dhaka City's Perspective. Current Urban Studies, 1, 19-27. doi: 10.4236/cus.2013.13003.

63. Oke T. R. Mills G. Christen A. Voogt J. A., 2017. Urban climates. Cambridge University Press.
64. Oyekola, M. Adewuyi K., 2018. Unsupervised Classification in Land Cover Types Using Remote Sensing and GIS Techniques.
65. Pal, S.; Ziaul, S., 2017. Detection of Land Use and Land Cover Change and Land Surface Temperature in English Bazar Urban Centre. Egypt. J. Remote Sens. Space Sci. 20, 125–145.
66. Parsaee M. Joybari M. M. Mirzaei P. A. Haghighat F. 2019. Urban heat island, urban climate maps and urban development policies and action plans. Environmental Technology & Innovation, 14.
67. Pramanik S. & Punia M., 2020. Land Use/Land Cover Change and Surface Urban Heat Island Intensity: Source—Sink Landscape-Based Study in Delhi, India. Environ. Dev. Sustain, 22, 7331–7356.
68. Priyankara, P.; Ranagalage, M.; Dissanayake, D.M.S.L.B.; Morimoto, T.; Murayama, Y., 2019. Spatial Process of Surface Urban Heat Island in Rapidly Growing Seoul Metropolitan Area for Sustainable Urban Planning Using Landsat Data (1996–2017). Climate. 7, 110.
69. Qin, Z.; Karnieli, A.; Berliner, P. A., 2001. Mono-Window Algorithm for Retrieving Land Surface Temperature from Landsat TM Data and Its Application to the Israel-Egypt Border Region. Int. J. Remote Sensing, 22, 3719–3746.
70. Rahman, K. & Zhang, D. (2018). Analyzing the Level of Accessibility of Public Urban Green Spaces to Different Socially Vulnerable Groups of People. Sustainability. [Online]. 10 (11). p.p. 3917. Available from: http://dx.doi.org/10.3390/su10113917.
71. Rahman, M. M. and Szabó, G. (2021) 'Impact of Land Use and Land Cover Changes on Urban Ecosystem Service Value in Dhaka, Bangladesh', Land. MDPI AG, 10(8), p. 793. doi: 10.3390/land10080793.
72. RAJUK, 2020. Detail Area Plan of Dhaka Metropolitan Area 2016-2035, Dhaka: Bangladesh Government Press.
73. Rigo G. Parlow E. Oesch D., 2006. Validation of satellite observed thermal emission with in-situ measurements over an urban surface, Remote Sensing of Environment, Volume 104, Issue 2, Pages 201-210, ISSN 0034-4257, https://doi.org/10.1016/j.rse.2006.04.018.
74. Rizwan A. M., Dennis L. Y. Chunho, L., 2008. A review on the generation, determination and mitigation of Urban Heat Island. Journal of the Environmental Sciences, 20(1), 120–128.

75. Schwarz N. Lautenbach S. Seppelt R., 2011. Exploring indicators for quantifying surface urban heat islands of European cities with MODIS land surface temperatures, Remote Sensing of Environment, Volume 115, Issue 12, Pages 3175-3186, ISSN 0034-4257, https://doi.org/10.1016/j.rse.2011.07.003.
76. Sejati A. W., Buchori I., Rudiarto. I., 2019. The spatio-temporal trends of urban growth and surface urban heat islands over two decades in the Semarang Metropolitan Region, Sustainable Cities and Society, Volume 46, 101432, ISSN 2210-6707, https://doi.org/10.1016/j.scs.2019.101432.
77. Shahmohamadi P. Che-Ani A., Ramly A. Maulud K. Mohd-Nor M., 2010. Reducing urban heat island effects: A systematic review to achieve energy consumption balance. International Journal of the Physical Sciences, 5(6), 626–636.
78. Sharma, R.; Joshi, P.K. Identifying Seasonal Heat Islands in Urban Settings of Delhi (India) Using Remotely Sensed Data—An Anomaly Based Approach. Urban Climate. 2014, 9, 19–34.
79. Shastri H. Ghosh S., 2019. Urbanisation and Surface Urban Heat Island Intensity (SUHII). In V. C, G, T. Mishra, & K. S (Eds.), Climate change signals and response. Singapore: Springer.
80. Siqi, J.; Yuhong, W., 2020. Effects of Land Use and Land Cover Pattern on Urban Temperature Variations: A Case Study in Hong Kong. Urban Clim. 34, 100693
81. Sobrino, J.A., Munoz, J.C., & Paolini, L. (2004). Land surface temperature retrieval from Landsat TM5. Remote Sensing of the Environment, 9, 434–440.
82. Stewart I. D., 2011. A systematic review and scientific critique of methodology in modern urban heat island literature. International Journal of Climatology, 31, 200-217.
83. Suriana D. Barkey R. A. Gou Z., 2020. Analysis of Land Use/Land Cover Change and Their Effects on Spatiotemporal Patterns Of Urban Heat Islands (UHI) In The City Of Makassar, Indonesia. International Journal of Engineering and Science Applications, Volume 7, ISSN 2406-9833.
84. Tariq T. Poerschke U. Iulo, L. 2022. Urban Heat Island Phenomena in Dhaka, Bangladesh.
85. Thanh Hoan, N., Liou, Y.-A., Nguyen, K.-A., Sharma, R., Tran, D.-P., Liou, C.-L. and Cham, D., 2018. Assessing the Effects of Land-Use Types in Surface Urban Heat Islands for Developing Comfortable Living in Hanoi City. Remote Sensing, [online] 10(12), p.1965. https://doi.org/10.3390/rs10121965.

86. The Independent. 2017. [Online] Available at: https://www.theindependentbd.com/arcprint/details/112836/2017-09-07 [Accessed 28 June 2022].
87. Tran D. X. Pla F. Carmona P.L. Myint S.W. Caetano M. Kieu H. V., 2017. Characterizing the relationship between land use land cover change and land surface temperature, ISPRS Journal of Photogrammetry and Remote Sensing, Volume 124, Pages 119-132, ISSN 0924-2716, https://doi.org/10.1016/j.isprsjprs.2017.01.001.
88. Tran D. X., Filiberto P., Pedro L.C, Soe W. M., Mario C., Hoan V. K., 2017. Characterizing the relationship between land use land cover change and land surface temperature, ISPRS Journal of Photogrammetry and Remote Sensing, Volume 124, Pages 119-132, ISSN 0924-2716, https://doi.org/10.1016/j.isprsjprs.2017.01.001.
89. UNDESA, 2015. (United nations, department of economic and social affairs, population division). World population prospects: the 2015 revision. In: Cohen, B., Pelletier, F., al, e. (Eds.), Methodology of the United Nations Population Estimates and Projections. No. ESA/P/WP, p. 242.
90. Verma R. and Garg P. K., 2021. "Multi-Temporal LU/LC Correlation in Lucknow City," IEEE International Geoscience and Remote Sensing Symposium IGARSS, 2021, pp. 6665-6668, doi: 10.1109/IGARSS47720.2021.9554958.
91. Voogt J A,Oke T R., 2003. Thermal remote sensing of urban climates. Remote Sensing of Environment 2003.
92. Wang, C., Myint, S., Wang, Z. and Song, J., 2016. Spatio-Temporal Modeling of the Urban Heat Island in the Phoenix Metropolitan Area: Land Use Change Implications. Remote Sensing, [online] 8(3), p.185. https://doi.org/10.3390/rs8030185.
93. Wang, Wenjie & Zhang, Chuanrong & Allen, Jenica & Li, Weidong & Boyer, Mark & Segerson, Kathleen & Silander, John. (2016). Analysis and Prediction of Land Use Changes Related to Invasive Species and Major Driving Forces in the State of Connecticut. Land. 5. 25. 10.3390/land5030025.
94. Weng Q., Mohammad Karimi Firozjaei, Amir Sedighi, Majid Kiavarz & Seyed Kazem Alavipanah (2019) Statistical analysis of surface urban heat island intensity variations: A case study of Babol city, Iran, GIScience & Remote Sensing, 56:4, 576-604, DOI: 10.1080/15481603.2018.1548080.

95. Weng, Q., Lu, D., & Schubring, J. (2004). Estimation of land surface temperature-vegetation abundance relationship for urban heat island studies. Remote Sensing of Environment, 89(4), 467–483.
96. Weng, Q., U. Rajasekar, and H. Xuefei. 2011. "Modeling Urban Heat Islands and Their Relationship with Impervious Surface and Vegetation Abundance by Using ASTER Images." IEEE Transactions on Geoscience and Remote Sensing 49 (10): 4080–4089. doi:10.1109/TGRS.2011.2128874.
97. Xiong Y, Huang S, Chen F, Ye H, Wang C, Zhu C., 2012. The Impacts of Rapid Urbanization on the Thermal Environment: A Remote Sensing Study of Guangzhou, South China. Remote Sensing. 4(7):2033-2056. https://doi.org/10.3390/rs4072033
98. Ying L. Yanwei S. Jialin L. Chao G., 2020. Socioeconomic drivers of urban heat island effect: Empirical evidence from major Chinese cities, Sustainable Cities and Society, Volume 63, 102425, ISSN 2210-6707, https://doi.org/10.1016/j.scs.2020.102425.
99. Yuan F. & Bauer M. E., 2008. Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery, Remote Sensing of Environment, Volume 106, Issue 3, Pages 375-386, ISSN 0034-4257, https://doi.org/10.1016/j.rse.2006.09.003.
100. Yuan, F.; Bauer, M.E. Comparison of Impervious Surface Area and Normalized Difference Vegetation Index as Indicators of Surface Urban Heat Island Effects in Landsat Imagery. Remote Sens. Environ. 2007, 106, 375–386.
101. Zhang H., Zhi-fang Qi, Xin-yue Ye, Yuan-bin Cai, Wei-chun Ma, Ming-nan Chen, 2013. Analysis of land use/land cover change, population shift, and their effects on spatiotemporal patterns of urban heat islands in metropolitan Shanghai, China, Applied Geography, Volume 44, Pages
102. Zhang X, Wang D, Hao H, Zhang F, Hu Y., 2017. Effects of Land Use/Cover Changes and Urban Forest Configuration on Urban Heat Islands in a Loess Hilly Region: Case Study Based on Yan'an City, China. International Journal of Environmental Research and Public Health.; 14(8):840. https://doi.org/10.3390/ijerph14080840
103. Zhang, X.; Estoque, R.C.; Murayama, Y., 2017. An Urban Heat Island Study in Nanchang City, China Based on Land Surface Temperature and Social-Ecological Variables. Sustain. Cities Soc. 32, 557–568.
104. Zhao L. Lee X. Smith R. B. Oleson K. 2014. Strong contributions of local background climate to urban heat islands. Nature, 511(7508), 216–219.

105. Zhao-Liang Li, Bo-Hui Tang, Hua Wu, Huazhong Ren, Guangjian Yan, Zhengming Wan, Isabel F. Trigo, Sobrino, J. A., 2013. Satellite-derived land surface temperature: Current status and perspectives, Remote Sensing of Environment. Volume 131, Pages 14-37, ISSN 0034-4257, https://doi.org/10.1016/j.rse.2012.12.008.
106. Zhou, X.; Wang, Y. C., 2011. Dynamics of Land Surface Temperature in Response to Land-Use/Cover Change. Geogr. Res. 49, 23–36.

CHAPTER 9: APPENDIX

Appendix I: Data of Socio-economic Variables and Mean NLST of Respective Thana

SL	Thana	Mean NLST Change	Decadal Growth Rate	Population Density	Density of Community Facilities	% of Affordable HH	% of HH with Electricity Connection 2011	HH Size 2011
1	Adabor	0.3032	135.72	63747.00	61.57	53.40	95.90	4.08
2	Badda	0.1244	49.37	15640.00	36.02	38.00	98.70	4.08
3	Biman Bandar Thana	0.1326	109.21	687.00	14.93	70.80	91.50	4.10
4	Cantonment	0.0664	12.26	13954.00	9.35	71.10	99.40	4.42
5	Darus Salam	0.1983	40.47	48371.00	68.42	39.20	97.80	3.94
6	Gulshan	0.0678	32.77	29187.00	51.62	47.70	99.10	4.14
7	Kafrul	0.1078	36.62	53036.00	51.75	47.90	99.00	4.09
8	Khilkhet	0.1926	139.25	16245.00	51.50	42.20	96.40	4.00
9	Mirpur	0.1610	-9.22	77940.00	89.06	60.70	99.20	4.20
10	Mohammadpur	0.1950	-21.97	43237.00	78.09	67.60	97.10	4.25
11	Pallabi	0.1404	38.39	59863.00	100.40	47.20	99.40	4.14
12	Ramna	0.0669	-21.90	54911.00	69.44	72.40	98.70	4.61
13	Rampura	0.1408	61.30	83925.00	55.34	68.40	99.30	4.41
14	Shah Ali	0.1059	42.28	29997.00	81.08	43.10	98.30	4.02
15	Sher-E-Bangla Nagar	0.0210	-7.10	30915.00	60.14	61.00	97.90	4.37
16	Tejgaon	0.0978	-50.93	58368.00	78.91	66.20	98.40	4.62
17	Tejgaon Industrial Area	0.0734	7.36	30761.00	83.60	45.00	98.60	3.93
18	Uttara	0.1273	-47.87	20101.00	77.90	80.50	93.50	4.39

(Source: BBS 2011 & USGS)

Appendix II: Data of Physical Variables and Mean NLST of Respective Thana

SL	THANAME	Mean NLST Change	Sum NDVI	Building Density	WB Density	Mean SVF	Percentage of Shadow Area
1	Adabor	0.3032	146.56	936.93	8.05	0.7225	22.34
2	Badda	0.1244	236.17	891.60	24.59	0.7685	22.61
3	Biman Bandar Thana	0.1326	634.96	187.29	58.92	0.9576	4.62
4	Cantonment	0.0664	597.45	216.84	28.87	0.9518	4.15
5	Darus Salam	0.1983	262.69	467.27	45.76	0.8663	12.47
6	Gulshan	0.0678	272.92	1022.04	27.43	0.7528	21.14
7	Kafrul	0.1078	571.40	616.76	22.28	0.8426	15.76
8	Khilkhet	0.1926	183.30	606.79	32.54	0.8160	15.55
9	Mirpur	0.1610	257.21	1180.38	4.60	0.6252	30.12
10	Mohammadpur	0.1950	284.73	923.76	7.75	0.7726	21.86
11	Pallabi	0.1404	267.94	980.26	12.34	0.7124	26.06
12	Ramna	0.0669	30.27	1165.65	29.02	0.6718	29.00
13	Rampura	0.1408	79.56	1121.37	22.73	0.6651	29.42
14	Shah Ali	0.1059	401.25	387.60	45.69	0.9125	9.29
15	Sher-E-Bangla Nagar	0.0210	184.45	472.46	14.82	0.8992	8.33
16	Tejgaon	0.0978	90.89	1113.01	4.86	0.7318	23.11
17	Tejgaon Industrial Area	0.0734	78.69	678.79	28.07	0.8347	12.08
18	Uttara	0.1273	192.64	1275.32	10.84	0.6614	31.26

(Source: RAJUK 2021 & USGS)